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Guide for Mechanistic-Empirical Design
OF NEW AND REHABILITATED PAVEMENT STRUCTURES

FINAL DOCUMENT

APPENDIX BB: DESIGN RELIABILITY

NCHRP

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Research into the subject area covered in this Appendix was conducted at both ARA-ERES and ASU. The authors of this Appendix are Mr. Jagannath Mallela, Dr. Manuel Ayres, Dr. Lev Khazanovich, Dr. Chetana Rao, Mr. Leslie Titus-Glover, Dr. Matthew Witczak and Dr. Michael Darter.

Foreword

This appendix describes the design reliability approach as incorporated into the design guide. It is a supporting reference to the performance model reliability discussions presented in PART 3, Chapters 3, 4, 6, and 7 of the Design Guide. Some equations and expressions presented in the referenced chapters are repeated here for emphasis and continuity.

The appendix begins with an introduction to the design reliability approach as incorporated into the design guide followed by its application to the rigid and flexible pavement design models.

Application to the rigid pavement design models includes: (1) the development of the variance models for estimating reliability of JPCP fatigue cracking, joint faulting, and smoothness models, and (2) the development of the variance models for estimating reliability of CRCP punchouts and smoothness models.

Application to flexible pavement design models includes the development of the variance models for estimating reliability of fatigue (bottom up) cracking, longitudinal (top down) cracking, rutting, thermal cracking, and smoothness models. Note that the same variance and reliability models are used for new pavement and rehabilitated pavement design.

DESIGN RELIABILITY

INTRODUCTION

Pavement design and construction is a very complex process that involves many uncertainties, variabilities, and approximations. Even though mechanistic concepts provide a more rational and realistic methodology for pavement design, a consistent and practical method to consider these uncertainties and variations is needed so that a new or rehabilitated pavement can be designed for a desired level of reliability.

Practically everything associated with the design of new and rehabilitated pavements is variable or uncertain in nature. Perhaps the most obviously uncertain of all is estimating truck axle loadings many years into the future. Materials and construction also introduce a measure of variability. Practically every existing pavement exhibits significant variation in condition along its length. Each of these variations must be considered properly in a reliability-based design. For the design to be effective, reliability must be incorporated in a consistent and uniform fashion for all pavement types and rehabilitation.

DESIGN RELIABILITY FOR JPCP FATIGUE CRACKING

The information presented in this section is applicable for new JPCP as well as for JPCP restoration and PCC overlays with JPCP.

Introduction

The definition of reliability for slab cracking for a given project under design is as follows:

R = P [Cracking of Design Project < Critical Level of Cracking Over Design Life]

The mean slab cracking (percent slabs) of the design project over time depends on many factors including the design of various aspects of the pavement and particularly joint spacing, slab thickness, strength of PCC, traffic loadings, climate (temperature gradients), construction curling, and climate during construction. Project slab cracking is a stochastic or probabilistic variable whose prediction is uncertain. For example, if 100 projects were designed and constructed with the same design and specifications, they would ultimately over time exhibit a wide range of slab cracking. Data from previous field studies shows that the coefficient of variation of mean slab cracking from project to project within a group of similar designs within a given state averaged 97 percent. ("Long-Term Pavement Performance Pre-Implementation Activities," technical report prepared for SHRP by J. B. Rauhut, M. I. Darter, R. L. Lytton, and R. E. DeVor, 1986.)

Mean slab cracking between similar projects follows some type of distribution. After considerable analyses, it is believed that the error in prediction of mean slab cracking is approximately normally distributed on the upper side of the mean cracking (not on the lower side, especially near zero cracking). Thus, the likely variation of cracking around the mean prediction can be defined by the mean of the prediction model (at any time over the design life) and a standard deviation. The standard deviation is a function of the error associated with the data used to calibrate the cracking model.

This memo summarizes development of the slab cracking design reliability procedure based on the normal distribution assumption. This procedure is based on analysis of the predicted versus measured cracking (see figure 1) and estimation of parameters of the corresponding error distribution.

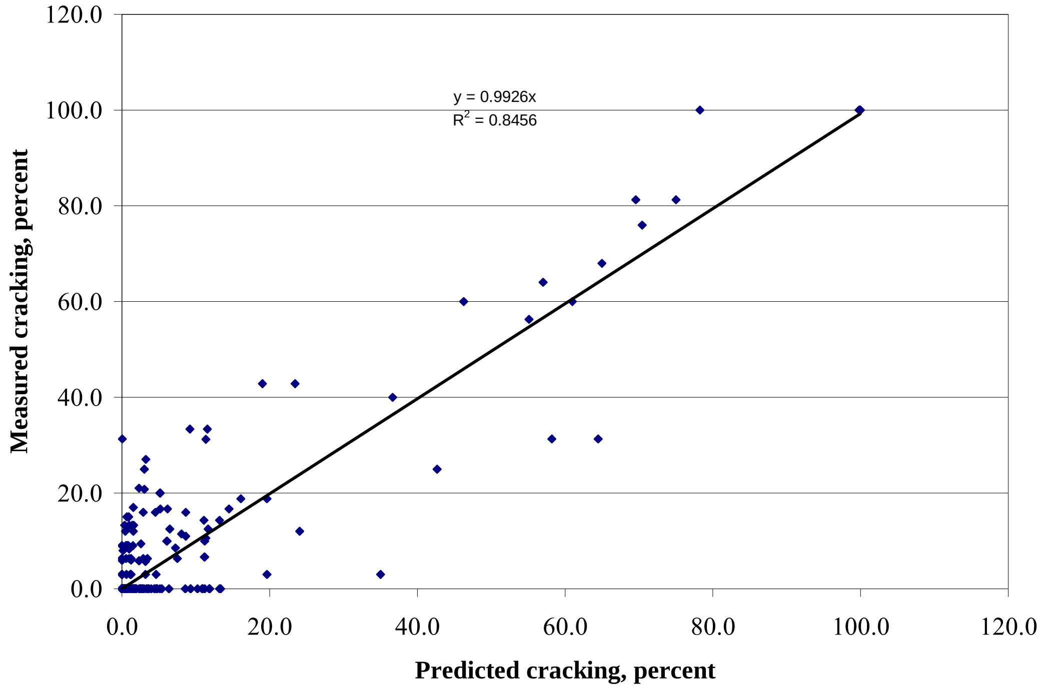

Figure 1. Predicted versus. measured JPCP cracking.

Step-by-Step Approach to Derive Parameters of the Error Distribution

<u>Step 1 – Group all data points by the level of predicted cracking</u>

All data points in the calibration database were divided into subgroups based on the level of predicted cracking. Table 1 shows the groups established after inspecting the data plots with residual (predicted – measured) on the y-axis versus predicted cracking on the x-axis (not shown here):

Table 1. Definition of groups for cracking data.

Group	Range of predicted cracking, percent	Number of data points
1	0 – 5	455
2	5-15	39
3	15 - 25	6
4	25 - 100	18

Step 2. Compute descriptive statistics for each group of data

For each predicted cracking group the following parameters were computed:

1. Mean predicted percentage of cracked slabs.
2. Mean measured percentage of cracked slabs.
2. Standard deviation of measured percentage of cracked slabs.

These parameters are presented in table 2.

Table 2. Computed statistical parameters for each cracking data group.

Group	Mean Predicted Cracking, percent	Mean Measured Cracking, percent	Standard Deviation of Measured Cracking, percent
1	0.404844	1.158024	3.837465
2	9.44674	8.940435	9.674352
3	20.32634	23.05238	16.40046
4	67.45885	65.41667	29.95126

Figure 2 shows very good correspondence between predicted and mean measured faulting for each group.

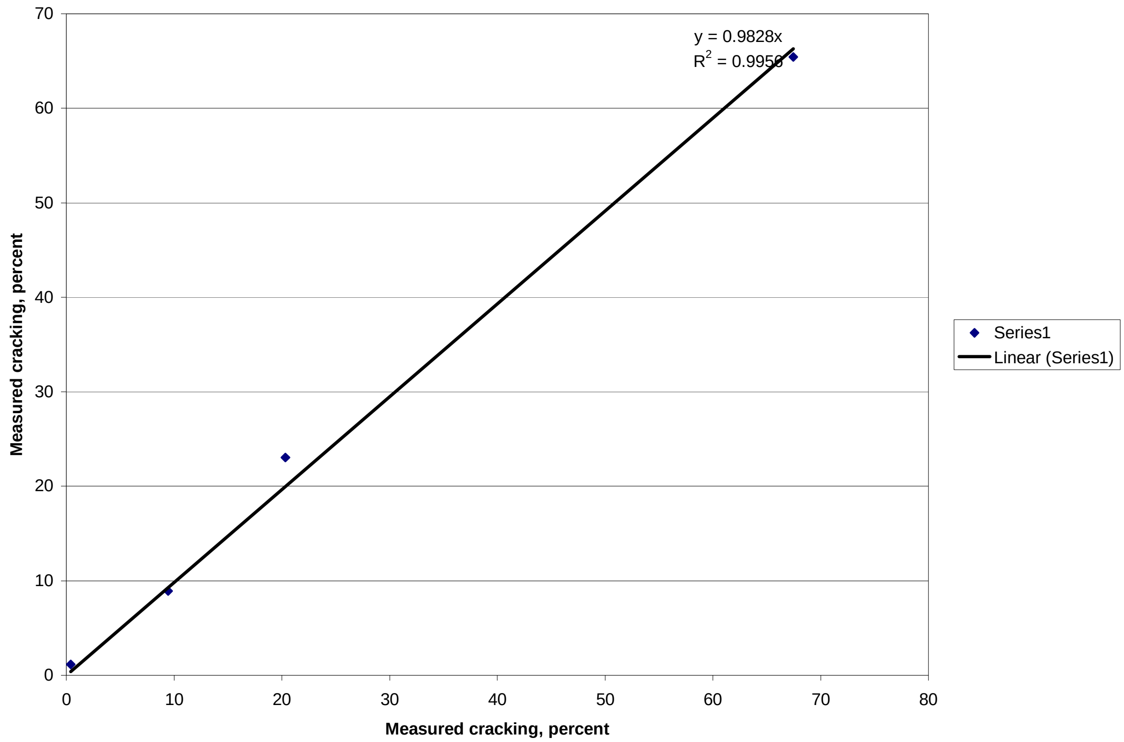

Figure 2. Mean predicted vs. mean measured cracking for each group of data.

Step 3. Determine relationship between standard deviation of the measured cracking and predicted cracking.

Based on data from table 2, the following relationship between standard deviation and predicted cracking was developed:

$$STDMeas = -0.0050568\ CRACK^2 + 0.7344222 * CRACK + 3.4276237 \qquad (1)$$

where

STDMeas = measured standard deviation
CRACK = predicted cracking, percent
R^2 = 99.9%
N = 4

Figure 3 shows relationship between standard deviation of measured cracking and predicted cracking.

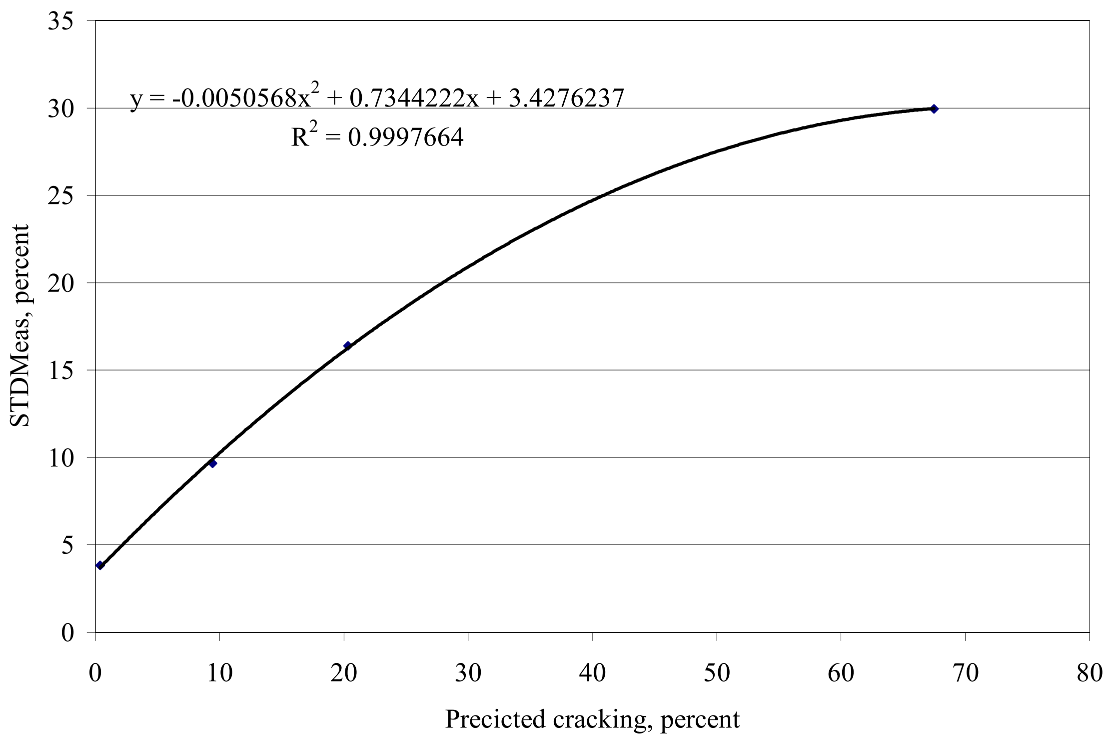

Figure 3. Standard deviation of measured cracking vs. predicted cracking (within each group)

Much discussion could be generated on what the STDMeas actually represents in terms of all the sources of variation of mean project cracking. It includes, among other sources, at least the following:

- Measurement error associated with slab cracking testing (this could be removed).
- Error associated with any inaccuracies in estimating the many inputs (PCC strength, layer thickness, consolidation of PCC around dowel bars, erosion of base, traffic loads, climate over life, and so on) for each of the calibration sections (while level 1 inputs were used for many inputs, others required level 2 or 3 as data was not available).
- Error associated with the cracking prediction algorithms used in the 2002 cracking models.

Step 4. Reliability analysis

Equation 1 permits a reliability analysis for predicted slab cracking to be conducted based on the results of the calibration and the deterministic analysis of cracking. The reliability analysis involves the following steps:

1. Using the 2002 Design Guide cracking model, predict the cracking level over the design period using mean inputs to the model. This corresponds approximately to a "mean" slab cracking due to symmetry of residuals.

2. Adjust mean cracking for the desired reliability level using the following relationship:

$$CRACK\_P = CRACK\_mean + STDmeas * Zp \qquad (2)$$

where

CRACK_P = cracking level corresponding to the reliability level p.

CRACK_mean = cracking predicted using the deterministic model with mean inputs (corresponding to 50 percent reliability).

STDmeas = standard deviation of cracking corresponding to cracking predicted using the deterministic model with mean inputs

Zp = standardized normal deviate (mean 0 and standard deviation 1) corresponding to reliability level p.

If adjusted cracking is calculated to be greater than 100 percent then the value of 100 percent should be set.

Figures 4 and 5 show predicted cracking for different reliability levels for the LTPP sections 124138, and 123811, respectively. One can see that an increase in reliability level leads to a reasonable increase in predicted cracking.

If a pavement designer wants a 90 percent reliability for slab cracking, then the predicted 90 percent curve must not exceed some preselected critical value of cracking. This level should be selected by the designer a priory to conducting the pavement design.

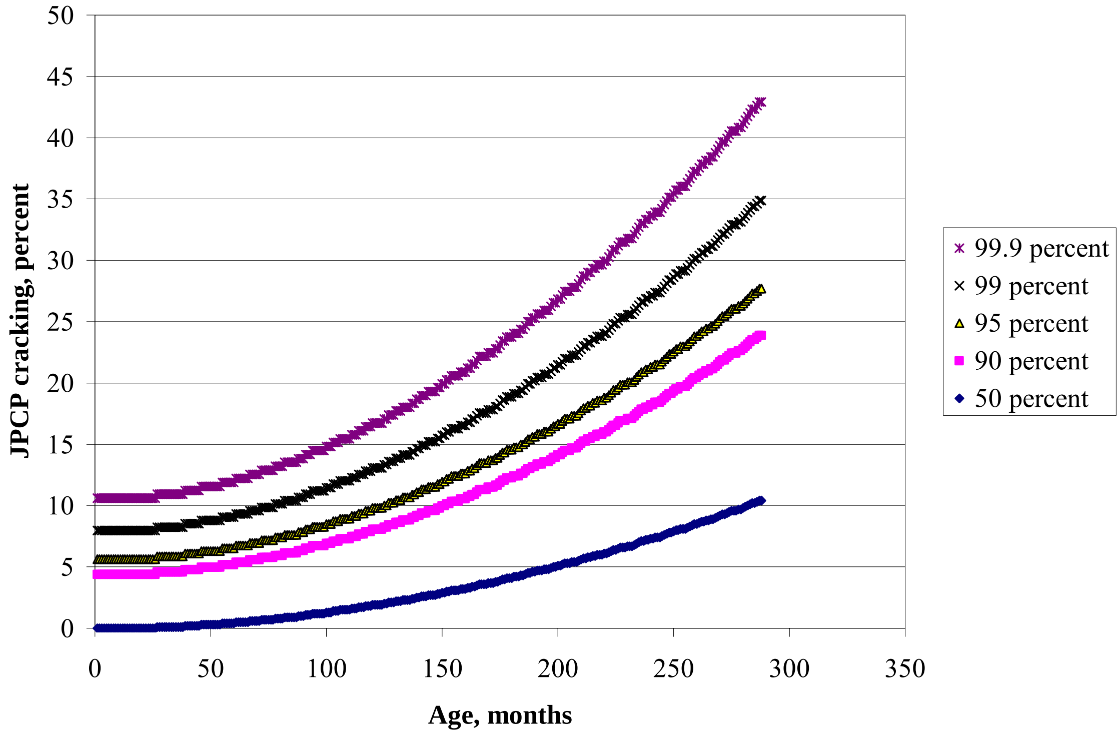

Figure 4. Predicted cracking for LTPP section 124138.

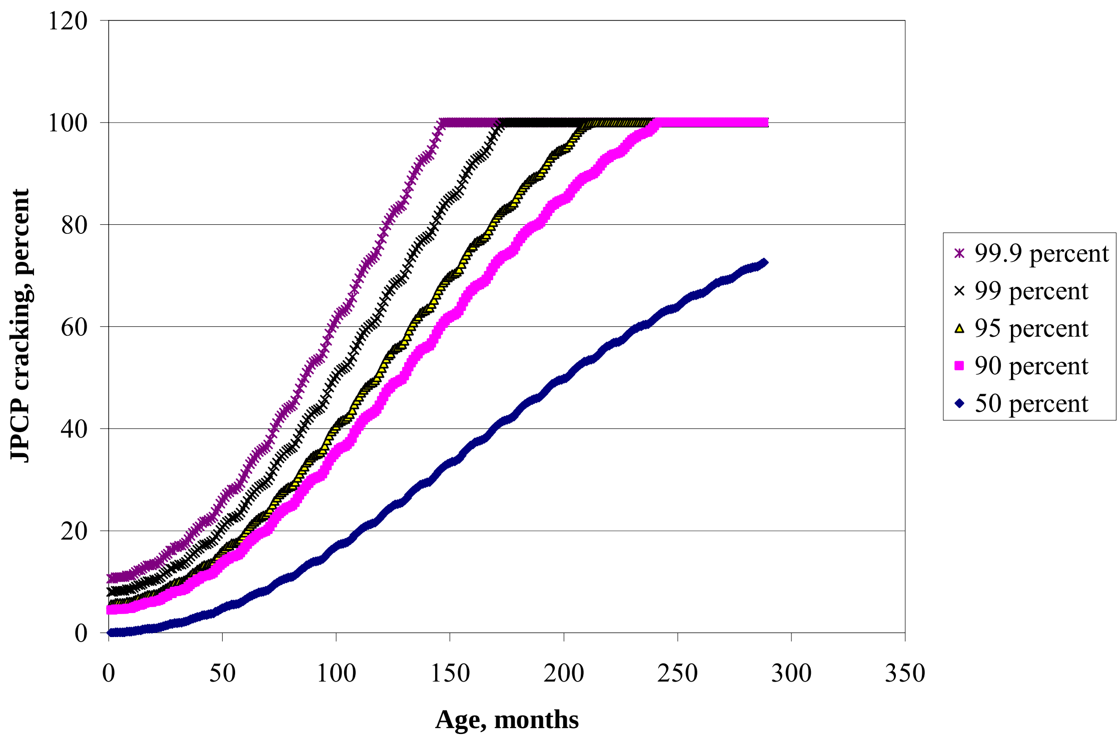

Figure 5. Predicted cracking at a given reliability level for LTPP section 123811.

For example, considering Figure 4.

> Mean predicted slab cracking at 50% reliability = 10 percent at 300 months.
> Predicted slab cracking for 90% reliability = 24 percent at 300 months.

Thus, a designer my state that he/she wants a joint design that is 90 percent reliable that it will not crack more than say 20 percent at the end of the 300 month design life. This design is not adequate for that criteria. Thus, the design must be altered so that the mean cracking is lower which will reduce each of the other curves until the design meets the performance criteria.

<u>Step 5. Impact of Level of Design Reliability for Slab Cracking</u>

The final step is to conduct a sensitivity analysis to see how realistic the various levels of reliability on project mean cracking. If a designer produces a design that at the 50^{th} percentile level predicts mean cracking at 10 percent as figure 4, is the cracking level at say the 90^{th} percentile level reasonable?

As an approximate independent test of reasonableness, the data quoted in the introduction showed a coefficient of cracking of about 97 percent between similar projects. Thus, given figure 4, if the mean slab cracking was 10 percent, this would have an associated standard deviation of 9.7 percent. The 90^{th} percent probability is reached at 1.3 * 9.7 + 10 = 22.6 percent cracking. Figure 4 shows the 90 percentile at about 24 percent which is close to 22.6 percent.

DESIGN RELIABILITY FOR JPCP FAULTING

The information presented in this section is applicable for new JPCP as well as for JPCP restoration and PCC overlays with JPCP.

Introduction

The definition of reliability for joint faulting for a given project under design is as follows:

R = P [Faulting of Design Project < Critical Level of Faulting Over Design Life]

The mean joint faulting of the design project over time depends on many factors including the design of various aspects of the pavement and particularly the joints, base erodibility, subdrainage, traffic, climate, construction quality of the joints, and climate during construction. Project joint faulting is a stochastic or probabilistic variable whose prediction is uncertain. For example, if 100 projects were designed and constructed with the same design and specifications, they would ultimately over time exhibit a wide range of joint faulting. Data from previous field studies shows that the coefficient of variation of mean joint faulting from project to project within a group of similar designs within a given state averaged 35 percent. ("Long-Term Pavement Performance Pre-Implementation Activities," technical report prepared for SHRP by J. B. Rauhut, M. I. Darter, R. L. Lytton, and R. E. DeVor, 1986.)

Mean joint faulting between similar projects follows some type of distribution. After considerable analyses, it is believed that the error in prediction of mean joint faulting is approximately normally distributed on the upper side of the mean faulting (not on the lower side, especially near zero faulting). Thus, the likely variation of joint faulting around the mean prediction can be defined by the mean of the prediction model (at any time over the design life) and a standard deviation. The standard deviation is a function of the error associated with the data used to calibrate the faulting model.

This memo summarizes development of the joint faulting design reliability procedure based on the normal distribution assumption. This procedure is based on analysis of the predicted versus measured faulting (see figure 6) and estimation of parameters of the corresponding error distribution.

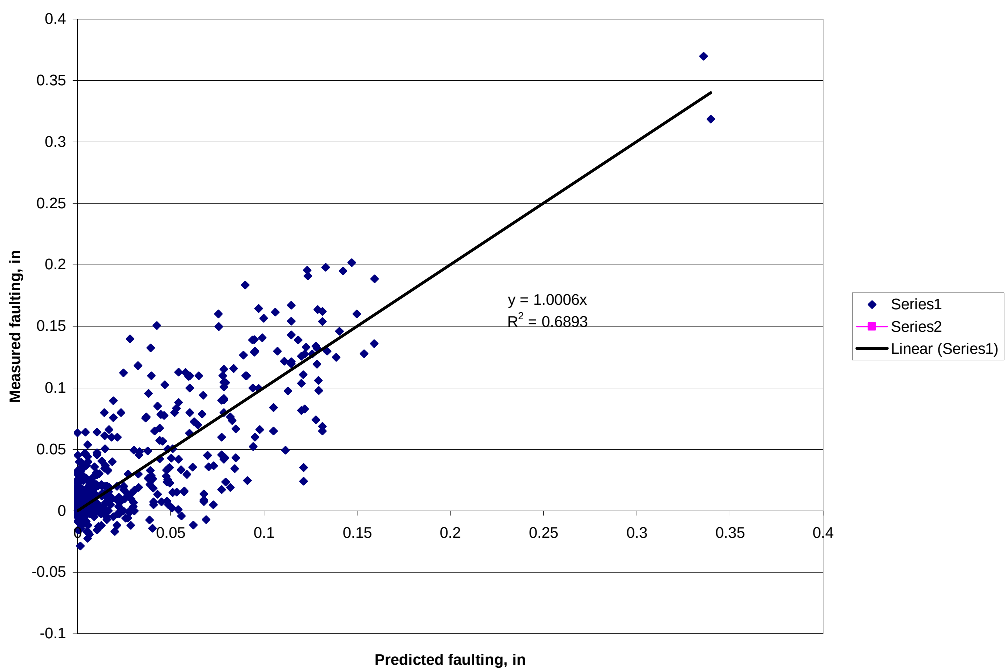

Figure 6. Predicted vs. measured faulting.

Step-by-Step Approach to Derive Parameters of the Error Distribution

<u>Step 1 – Group all data points by the level of predicted faulting</u>

All data points in the calibration database were divided into subgroups based on the level of predicted faulting. Table 3 shows the groups established after inspecting the data plots with the residual (predicted – measured) on the y-axis versus predicted faulting on the x-axis:

Table 3. Definition of faulting groups

Group	Range of predicted faulting, in	Number of data points
1	0 – 0.01	289
2	0.01 – 0.03	123
3	0.03 – 0.05	53
4	0.05 – 0.1	80
5	0.1 – 0.15	46

<u>Step 2. Compute descriptive statistics for each group of data</u>

For each predicted faulting group the following parameters were computed:

1. Mean predicted faulting, in
2. Mean measured faulting, in
3. Standard deviation of measured faulting, STDMeas, in

These parameters are presented in table 4.

Table 4. Computed statistical parameters for each faulting group.

Group	Mean Predicted Faulting, in	Mean Measured Faulting	Standard Deviation of Measured Faulting
1	0.002473	0.008171	0.013854
2	0.015071	0.015988	0.025465
3	0.039882	0.04289	0.039594
4	0.073545	0.070437	0.047311
5	0.126054	0.125603	0.04337

Figure 7 shows very good correspondence between predicted faulting and mean measured faulting for each group.

<u>Step 3. Determine the relationship between standard deviation of the measured faulting and predicted faulting</u>

Based on data from table 4, the following relationship between variance and predicted faulting was derived:

$$STDMeas = (0.0023980 - \exp(-317.88385 * FAULT^2 - 12.81805 * FAULT^{-0.07957})))^{1/2} \quad (3)$$

where

STDMeas = measured standard deviation of faulting, in
FAULT = predicted faulting, in
$R^2 = 98.4\%$
N = 5

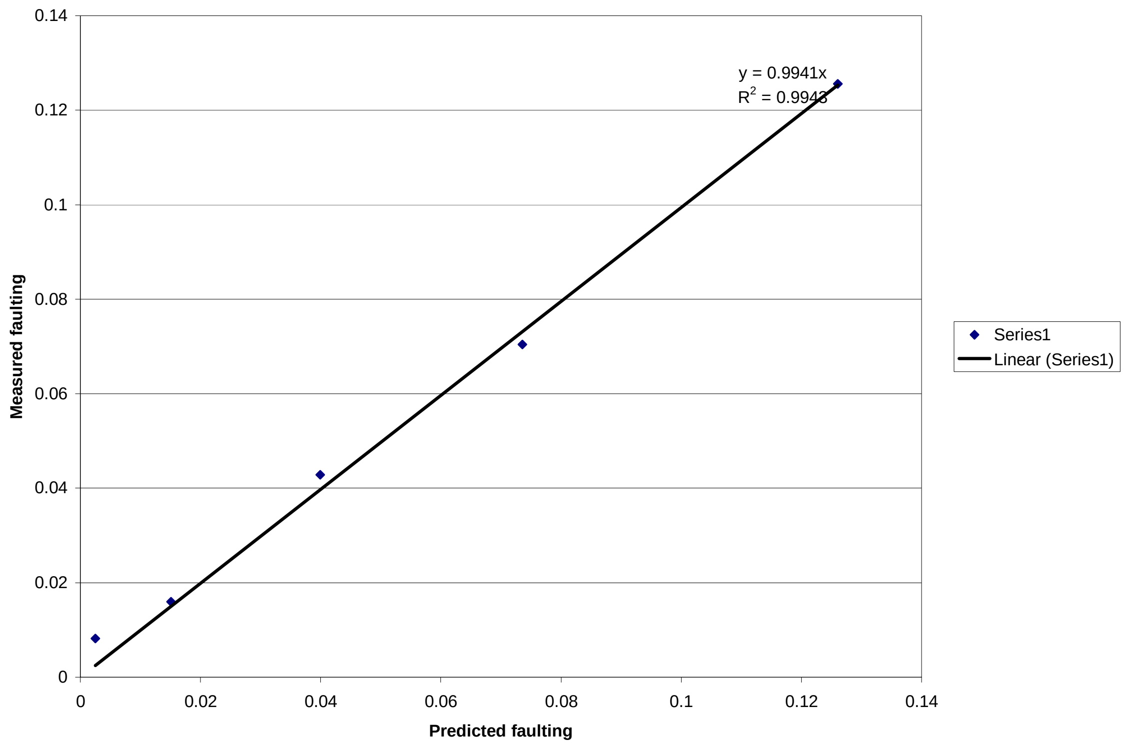

Figure 7. Mean predicted vs. mean measured faulting for each group of data.

Much discussion could be generated on what the STDMeas actually represents in terms of all the sources of variation of mean project joint faulting. It includes, among other sources, at least the following variation:

- Measurement error associated with joint faulting testing (this could be removed).
- Error associated with any inaccuracies in estimating the many inputs (PCC strength, layer thickness, consolidation of PCC around dowel bars, erosion of base, traffic loads, climate over life, and so on) for each of the calibration sections (while level 1 inputs were used for many inputs, others required level 2 or 3 as data was not available).
- Error associated with the faulting prediction algorithms used in the 2002 faulting models.

Step 4. Reliability analysis

Equation 4 permits a reliability analysis for predicted joint faulting to be conducted based on the results of the calibration and the deterministic analysis of faulting. The reliability analysis involves the following steps:

1. Using the 2002 Design Guide faulting model, predict the faulting level over the design period using mean inputs to the model. This corresponds approximately the a "mean" joint faulting due mean inputs and symmetry of residuals.

2. Adjust mean faulting for the desired reliability level using the following relationship:

$$FAULT\_P = FAULT\_mean + STDmeas * Zp \qquad (4)$$

where

FAULT_P = faulting level corresponding to the reliability level p.

FAULT = faulting predicted using the deterministic model with mean inputs (corresponding to 50 percent reliability).

STDmeas = standard deviation of faulting corresponding to faulting predicted using the deterministic model with mean inputs

Zp = standardized normal deviate (mean 0 and standard deviation 1) corresponding to reliability level p.

This model was applied to data from three LTPP sections. Figures 8, 9, and 10 show predicted faulting for different reliability levels for the LTPP sections 013028, 123804, and 553009, respectively. For each JPCP section, one can see that as the reliability level increases, the predicted faulting level also increases according to equation 4.

If a pavement designer wants a 90 percent reliability for joint faulting, then the predicted 90 percent curve must not exceed some preselected critical value of joint faulting. This level should be selected by the designer a priory to conducting the pavement design.

For example, considering Figure 8.

Mean predicted joint faulting at 50% reliability = 0.10 in at 240 months.
Predicted joint faulting for 90% reliability = 0.16 in at 240 months.

Thus, a designer my state that he/she wants a joint design that is 90 percent reliable that it will not fault more than say 0.15 in at the end of the 240 month design life. This design is not adequate for that criteria. Thus, the design must be altered so that the mean faulting is lower which will reduce each of the other curves until the design meets the performance criteria.

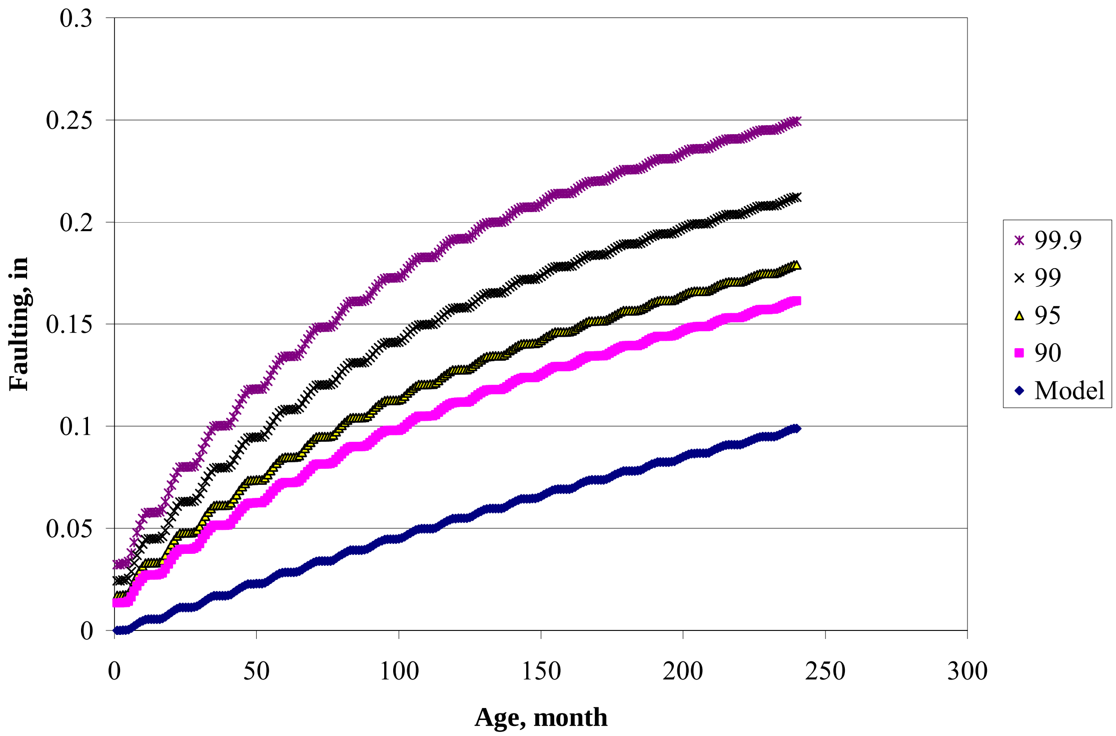

Figure 8. Predicted faulting for section 013028 with no dowel bars.

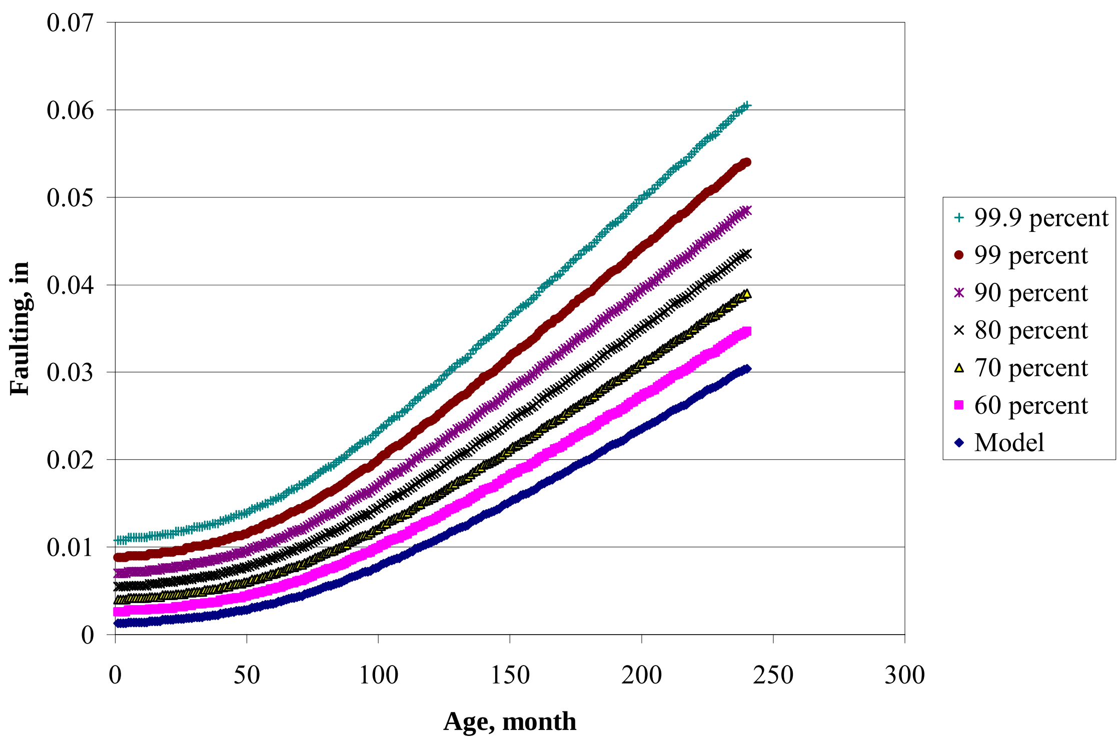

Figure 9. Predicted faulting for section 123804 with dowel bars.

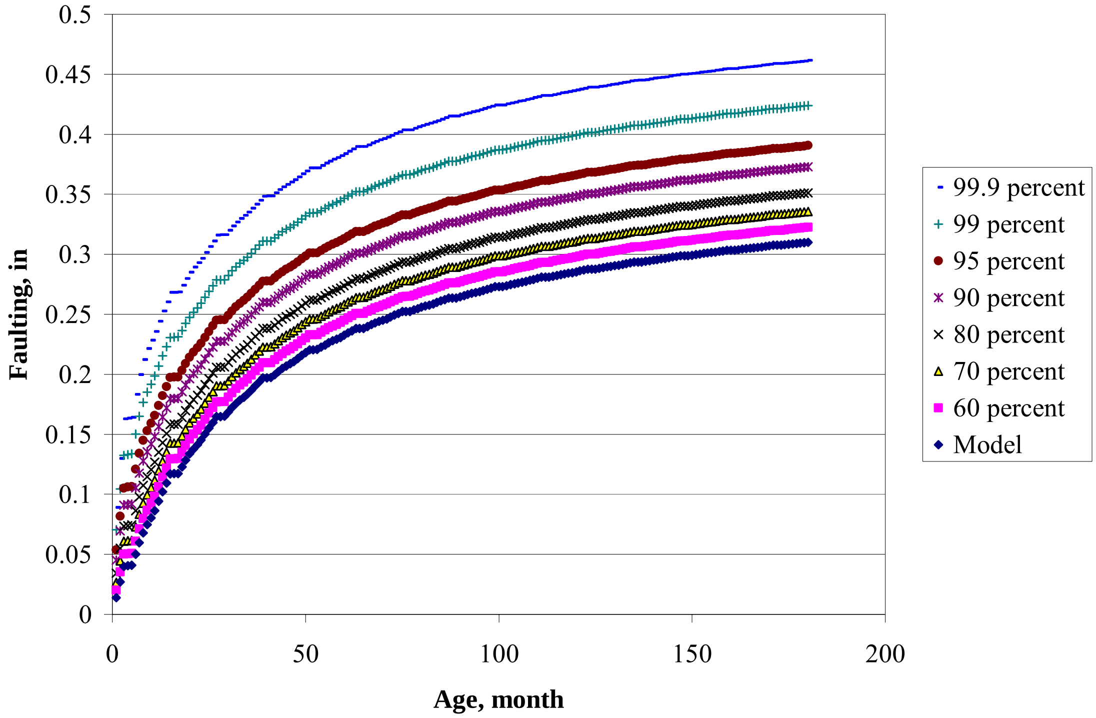

Figure 10. Predicted faulting at a given reliability level for section 553009 which contains no dowels.

Step 5. Impact of Level of Design Reliability for Joint Faulting

The final step is to conduct a sensitivity analysis to see how realistic the various levels of reliability on project mean joint faulting. If a designer produces a design that at the 50th percentile level predicts mean faulting at 0.1 in as figure 8, is the faulting level at say the 90th percentile level reasonable?

As an approximate independent test of reasonableness, the data quoted in the introduction showed a coefficient of faulting of about 35 percent between similar projects. Thus, given figure 8, if the mean joint faulting was 0.10 in, this would have an associated standard deviation of 0.035 in. The 90th percent probability is reached at 1.3 * 0.035 + 0.10 = 0.146 in. Figure 8 shows the 90 percentile at about 0.16 in which is close to 0.146 in. faulting.

DESIGN RELIABILITY FOR CRCP PUNCHOUTS

Introduction

The definition of reliability for CRCP punchouts for a given project under design is as follows:

R = P [Punchouts of Design Project < Critical Level of Punchouts Over Design Life]

The mean number of punchouts of the design project over time depends on many factors including slab thickness, percentage of reinforcement, base erodibility, traffic loadings, climate, construction quality, and even climate during construction. The number of punchouts that occur on a project is a stochastic or probabilistic variable whose prediction is uncertain. For example, if 100 projects were designed and constructed with the same design and specifications, they would ultimately over time exhibit a wide range of number of punchouts per unit length. Unfortunately there is no valid data from previous field studies to provide an estimate of the coefficient of variation of the number of punchouts from project to project within a group of similar designs within a given state. Based on observed field punchout data the CV is expected to be similar to that for cracking of JPCP which was 97 percent from the following study: "Long-Term Pavement Performance Pre-Implementation Activities," technical report prepared for SHRP by J. B. Rauhut, M. I. Darter, R. L. Lytton, and R. E. DeVor, 1986.

The number of punchouts per unit length between similar projects follows some type of distribution. After considerable analyses with various distributions (Weibull, Beta, Normal), and for practical reasons, it is believed that the error in prediction of mean number of punchouts of a project can be reasonably represented by a normal distribution within the range of interest. Extensive attempts to implement the Weibull distribution with upper and lower boundaries proved to be impractical. Using the normal distribution, the likely variation of number of punchouts around the mean prediction can be reasonably defined by the mean estimate of the punchout model (at any time over the design life) and a standard deviation. The standard deviation is determined from the field calibration results for the punchout model.

This memo summarizes development of the design reliability procedure for CRCP punchouts based on the normal distribution assumption for the residual error. This procedure is based on analysis of the predicted versus measured punchouts (see figure 11). The predicted minus measured punchouts for a given CRCP section represents the residual error of prediction. The residuals of prediction (as noted by the scatter in figure 1) represents all available information on the ways the fitted model fails to properly explain the observed variation in the measured punchouts from the given field calibration data set. This data consists mostly of LTPP GPS-5 CRCP sections from throughout the United States.

Step-by-Step Approach to Derive Parameters of the Error Distribution

<u>Step 1 – Group all data points by the level of predicted number of punchouts</u>

All data points in the calibration database were divided into subgroups based on the level of predicted punchouts. Table 5 shows the groups established after inspecting the data plots with the residual (predicted – measured) on the y-axis versus predicted number of punchouts on the x-axis.

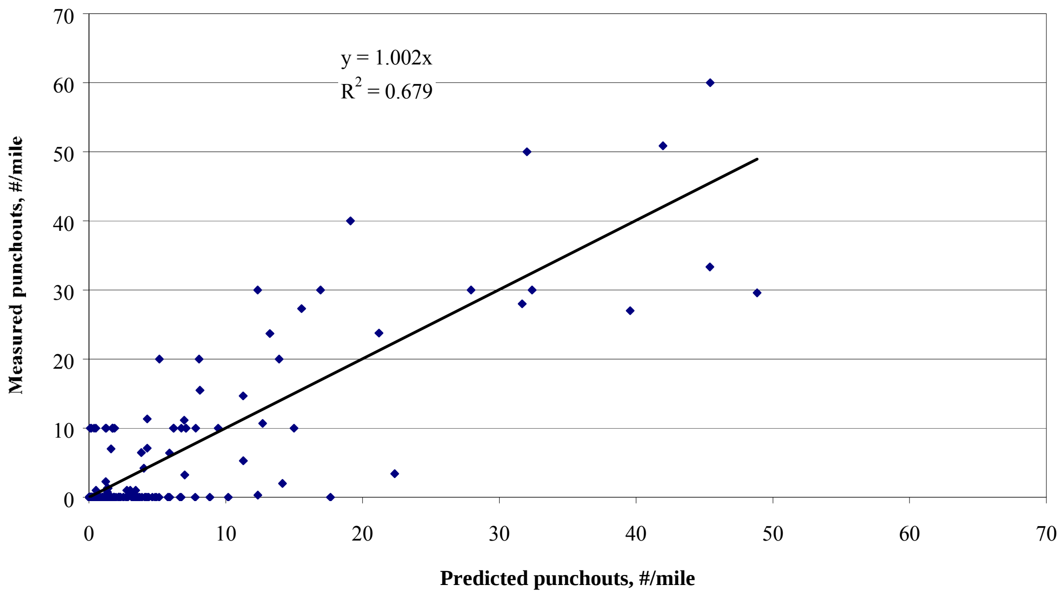

Figure 11. Predicted vs. measured punchouts based on final calibration for CRCP

Table 5. Definition of punchout groups.

Group	Range of predicted number of punchouts	Number of data points
1	0 – 0.2	49
2	0.2 – 1.3	55
3	1.3 – 20	104
4	20-100	12

Step 2. Compute descriptive statistics for each group of data

For each predicted punchout group the following parameters were computed:

1. Mean predicted number of punchouts, punchouts/mile
2. Mean measured number of punchouts, punchouts/mile
3. Standard deviation of measured number of punchouts, punchouts/mile

These parameters are presented in table 6.

Table 6. Computed statistical parameters for each punchout group.

Group	Mean Predicted Number of Punchouts/mi	Mean Measured Number of Punchouts/mi	Standard Deviation of Measured Number of Punchouts/mi
1	0.0996	0.4082	1.9991
2	0.6976	0.7865	2.6250
3	4.9440	4.2622	7.8145
4	34.1645	35.4975	16.6353

Figure 12 shows reasonable correspondence between predicted punchouts and mean measured punchouts for each group at least for the higher two group means. If these means do not agree reasonably, adjustments should be made to the group limits until acceptable agreement is reached.

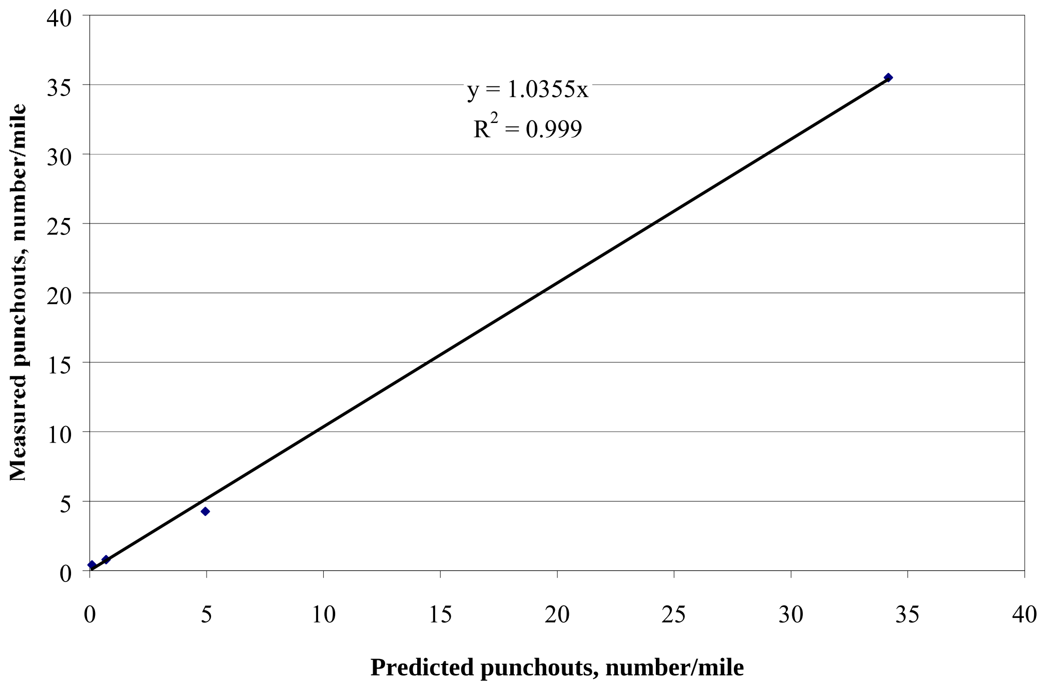

Figure 12. Mean predicted vs. mean measured punchouts for each group of data.

<u>Step 3. Determine the relationship between standard deviation of the measured punchouts and predicted punchouts.</u>

Based on data from table 6, the following relationship between standard deviation and predicted punchouts was derived using least squares regression:

$$STDMeas = 4.04*PUNCHOUT^{0.3825} \quad (5)$$

where

STDMeas = measured standard deviation of punchouts, punchouts/mile
PUNCHOUT = predicted number of punchouts, punchouts/mile
R^2 = 95.7%
N = 4

Figure 13 shows relationship between predicted punchouts and measured standard deviation. The standard deviation increases and then levels off with increased predicted punchouts. The COV of predicted punchouts is fairly high, in the order of 100 percent over some ranges of prediction which is what was expected due to the many sources of error involved. Figure 14 shows the relationship between measured and predicted standard deviation of punchouts. This relationship should be close to a one to one line.

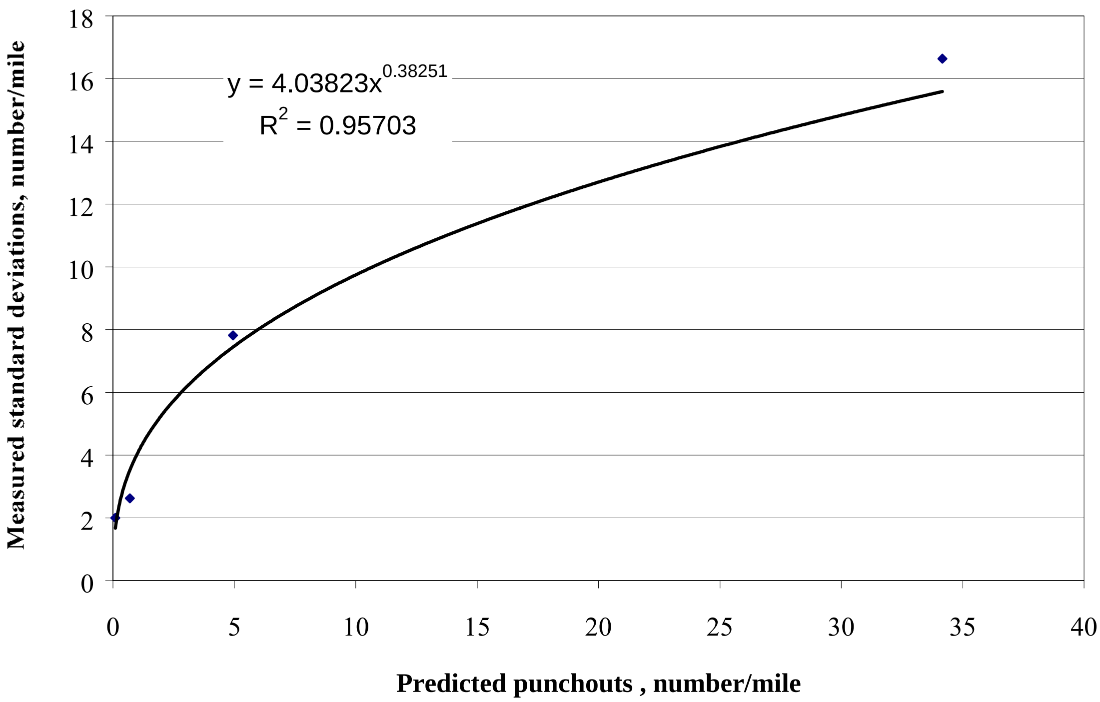

Figure 13. Predicted number of punchouts vs. mean measured standard deviation number of punchouts for each group of data.

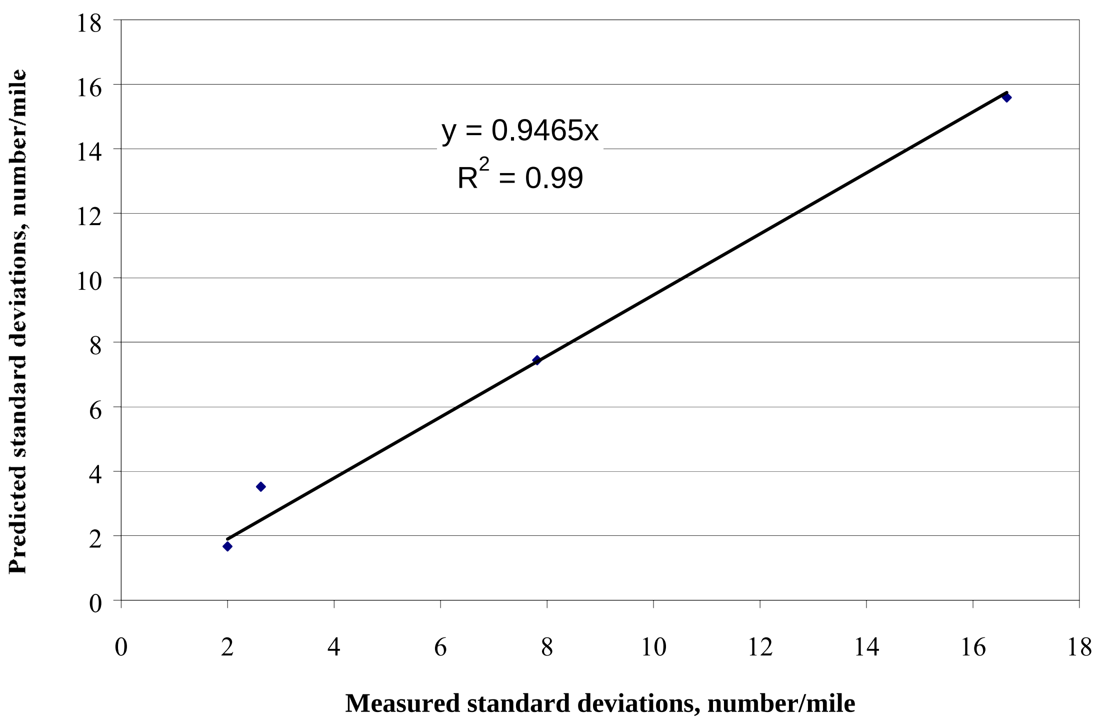

Figure 14. Predicted standard deviation vs. mean measured standard deviation number of punchouts for each group of data.

Much discussion could be generated on what the STDMeas actually represents in terms of all the sources of variation of mean project number of punchouts. It includes, among other sources, at least the following variation:

- Measurement error associated with field surveys that "measure" the number of punchouts testing (this source could be estimated and removed).
- Error associated with any inaccuracies in estimating the many inputs (percentage of reinforcement, PCC strength, layer thickness, erosion of base, traffic loads, climate over life, and so on) for each of the calibration sections (while level 1 inputs were used for many inputs, others required level 2 or 3 as data was not available).
- Error (or limitations) associated with the mechanistic based punchout prediction algorithms used in the 2002 Design Guide punchout models.
- Pure error between the performance of replicate CRCP sections in the field (similar to differences in replicate concrete cylinder tests).

One clear source of error that is not included in the error is uncertainty in estimation is growth of traffic over the design life for a new design or rehabilitation project. There are likely others that are not included, or that are not included in the proper magnitude.

<u>Step 4. Reliability analysis</u>

Equation 5 permits a reliability analysis for predicted number of punchouts to be conducted based on the results of the calibration and the deterministic analysis of punchouts. The reliability analysis involves the following steps:

1. Using the 2002 Design Guide CRCP punchout model, predict the punchout level over the design period using mean inputs to the model. This corresponds approximately the "mean" number of expected punchouts due to mean inputs and symmetry of residuals.
2. Adjust the mean number of punchouts per mile for the desired reliability level using the following relationship:

$$PUNCHOUT\_P = PUNCHOUT\_mean + STDmeas * Zp \qquad (6)$$

where

PUNCHOUT _P = punchout level corresponding to the reliability level p.

PUNCHOUT_mean = punchout predicted using the deterministic model with mean inputs (corresponding to 50 percent reliability).

STDmeas = standard deviation of faulting corresponding to faulting predicted using the deterministic model with mean inputs

Zp = standardized normal deviate (mean 0 and standard deviation 1) corresponding to reliability level p.

Step 5. Impact of Level of Design Reliability for CRCP Punchouts

This model was applied to data from three LTPP sections to illustrate the impact. Figures 15, 16, and 17 show predicted punchouts for different reliability levels for the LTPP sections 015008, 175020, and 375037, respectively. For each CRCP section, one can see that as the reliability level increases, the predicted punchout level also increases according to equation 2.

If a pavement designer wants a 90 percent reliability for number of punchouts, then the predicted 90 percent curve for the project must not exceed some preselected critical value of number of punchouts. This level should be selected by the designer a priory to conducting the pavement design. The critical design value and the design reliability level should be considered together to avoid the unreasonable selection of one or the other. For example, a designer might select a low critical level value, say 2 punchouts/mile at a high reliability level, say 99 percent. This might be difficult or impossible to achieve in with the design procedure.

One additional consideration is to conduct a sensitivity analysis to see how realistic the various levels of design reliability on project mean punchouts. For example, consider the section in figure 16. If a designer produces a design that at the 50^{th} percentile level predicts mean punchouts at 0.2 per mile, is the punchout level at say the 90^{th}, 95^{th}, and 99^{th} percentile levels reasonable? In this case, these values are and they appear reasonable (e.g., if 100 CRCP projects are built and the average punchouts per mile at the end of the design life was 0.2, it is conceivable that 5 of these project exhibited more than 3.8 punchouts per mile).

3.2 per mile at 90 percent
4.1 per mile at 95 percent
5.7 per mile at 99 percent

Also, if the design does not meet the cracking criteria at say 90 percent, are the changes in the design required to meet the desired reliability reasonable? This would require changes in CRCP thickness, percent reinforcement, base type or material erosion potential, tied-PCC shoulder, and others.

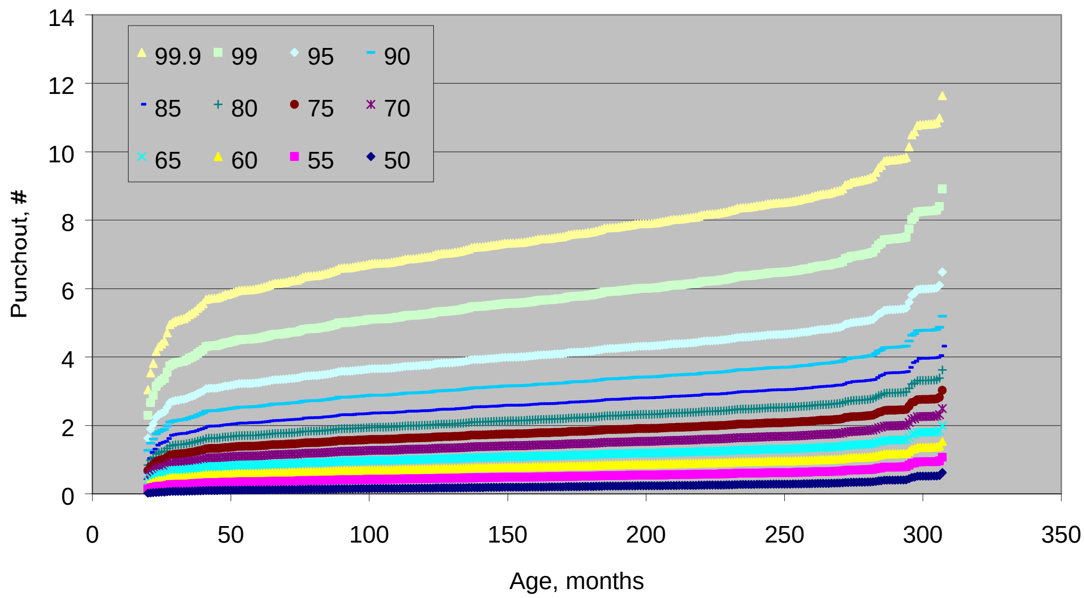

Figure 15. Predicted number of punchouts for LTPP section 015008.

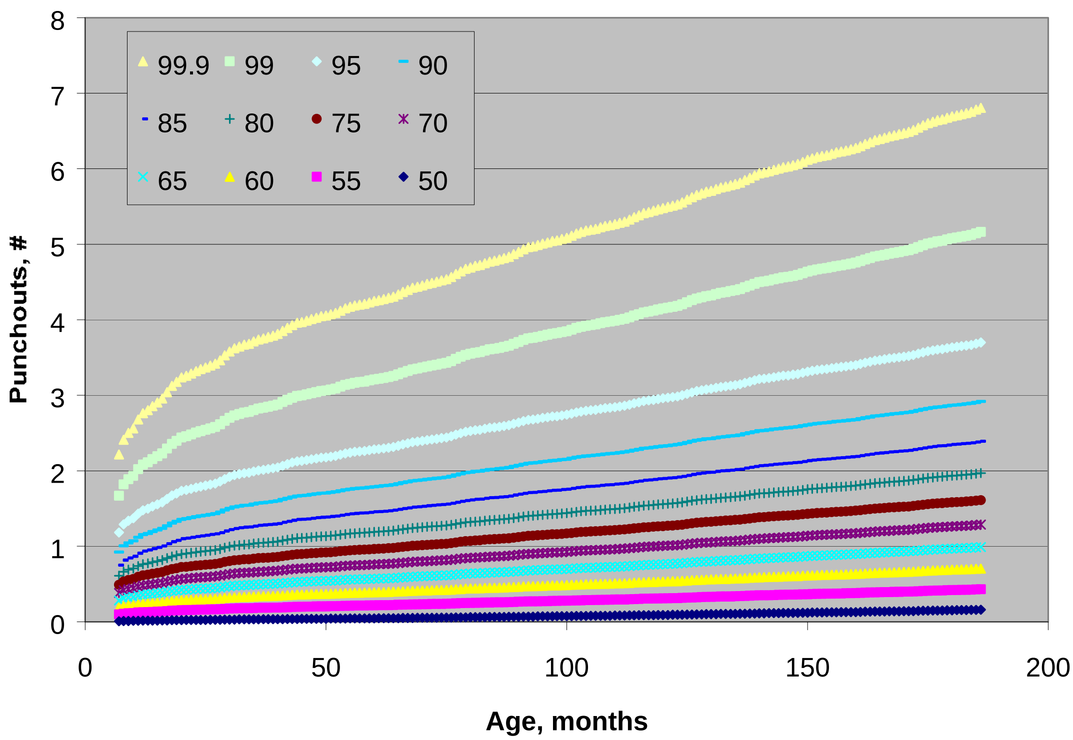

Figure 16. Predicted number of punchouts for LTPP section 175020.

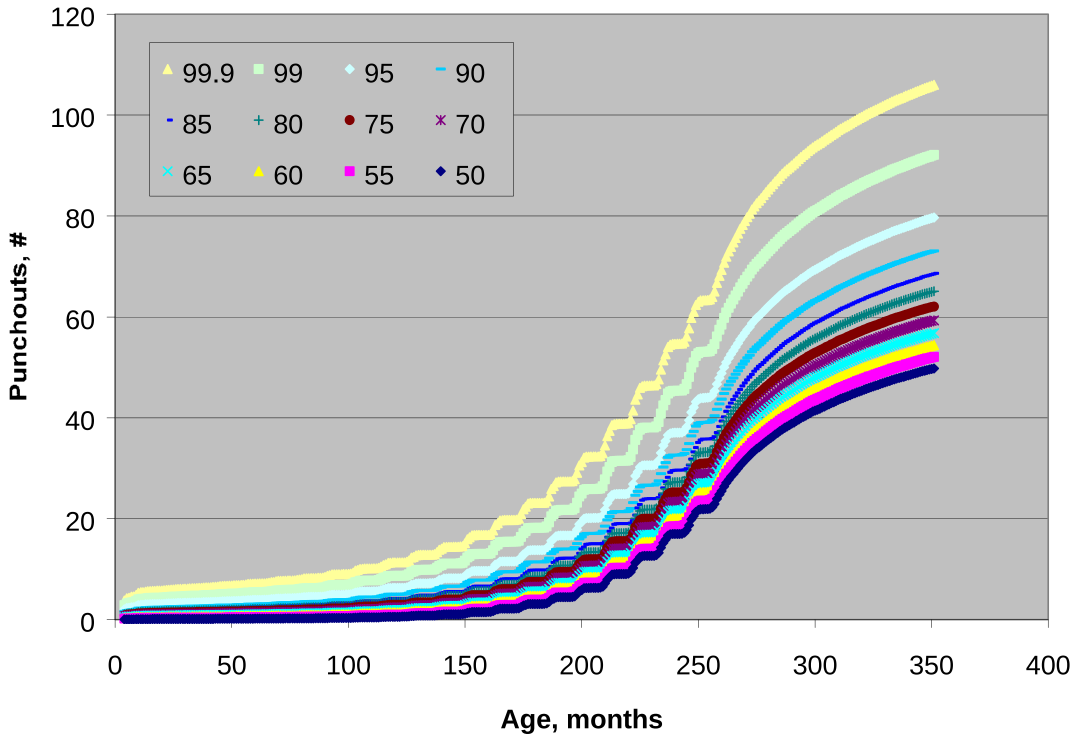

Figure 17. Predicted number of punchouts for LTPP section 375037.

DESIGN RELIABILITY FOR AC FATIGUE (BOTTOM UP) CRACKING

The information presented in this section is applicable for new as well as rehabilitated flexible and semi-rigid pavement structures.

Introduction

The definition of reliability for AC fatigue cracking for a given project under design is as follows:

R = P [Fatigue Cracking of Design Project < Critical Level of Fatigue Cracking Over Design Life]

where:

R is the reliability level
P is the probability

The expected (average) fatigue cracking as percent of wheel path area (2.6ft x 500ft x 2) of the design project over time is assumed to depend on the tensile strains at the bottom of the bound layers and, consequently, on all conditions affecting this pavement response. Fatigue cracking is a stochastic or probabilistic variable whose prediction is uncertain. For example, if 100 projects were designed and built with the same design and specifications, they would ultimately exhibit a wide range of fatigue cracking over time.

Average AC fatigue cracking between similar projects follows a certain probability distribution. It was assumed that the expected percentage of fatigue cracking is approximately normally distributed on the higher (greater than mean) side of the probability distribution (not on the lower side, particularly near zero cracking). Thus, the likely variation of cracking around the expected level estimated can be defined by the mean of the prediction model (at any time over the design life) and a standard deviation. The standard deviation is a function of the error associated with the predicted cracking and the data used to calibrate the fatigue cracking (bottom up) model.

This part summarizes the development of the reliability approach for flexible pavement fatigue cracking based on the normal distribution assumption. This procedure is based on analysis of the predicted versus measured cracking (see Figure 18) and estimation of parameters of the corresponding error distribution.

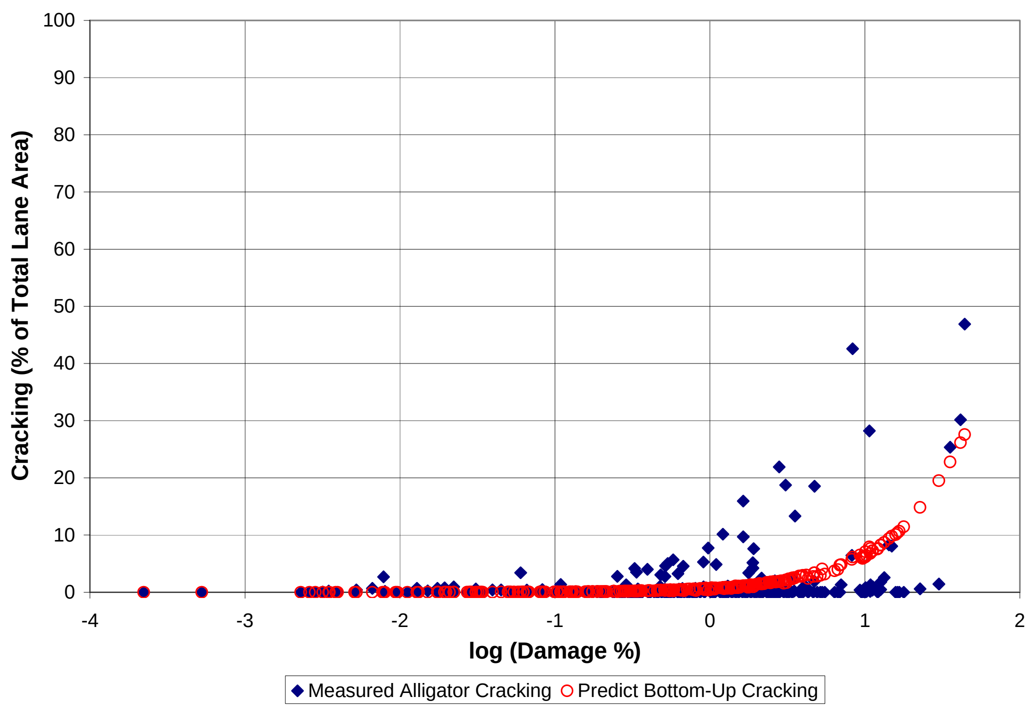

Figure 18. Predicted versus measured asphalt concrete bottom up fatigue cracking.

Step-by-Step Approach to Derive Parameters of the Error Distribution

Step 1 – Group all data points by the level of predicted cracking

All data points in the calibration database were divided into subgroups based on the level of predicted cracking. Table 7 shows the groups established after inspecting the data plots with residual (predicted – measured) on the y-axis versus predicted cracking on the x-axis (not shown here):

Table 7. Definition of groups for AC fatigue cracking data.

Group	Range of Predicted log(Damage(%))	Number of Data Points
1	< -2	18
2	-2 to -1	47
3	-1 to 0	161
4	0 to 1	158
5	> 1	77

<u>Step 2. Compute descriptive statistics for each group of data</u>

For each predicted cracking group the following parameters were computed:

1. Predicted fatigue cracking damage (each section and group average).
2. Predicted fatigue cracking (each section).
3. Measured fatigue cracking (each section).
4. Standard error of estimate for fatigue cracking (each group).

The summary of this analysis is in Table 8.

Table 8. Computed statistical parameters for each data group (fatigue cracking).

Group	Average Predicted log(Damage(%))	Standard Deviation of Measured Cracking, percent
1	0.502287	0.681458
2	0.552151	0.562037
3	1.281312	1.811323
4	6.493843	6.224589
5	11.56308	12.04897

<u>Step 3. Determine relationship for the standard error of estimate for fatigue cracking.</u>

Based on data from Table 8, the following relationship was developed (Figure 19):

$$Se_{FC} = 0.5+12/(1+e^{1.308-2.949*\log D}) \qquad (7)$$

where

Se_{FC} = standard error of estimate for bottom up fatigue cracking
D = predicted damage for bottom up fatigue cracking
R^2 = 94.7%
N = 5

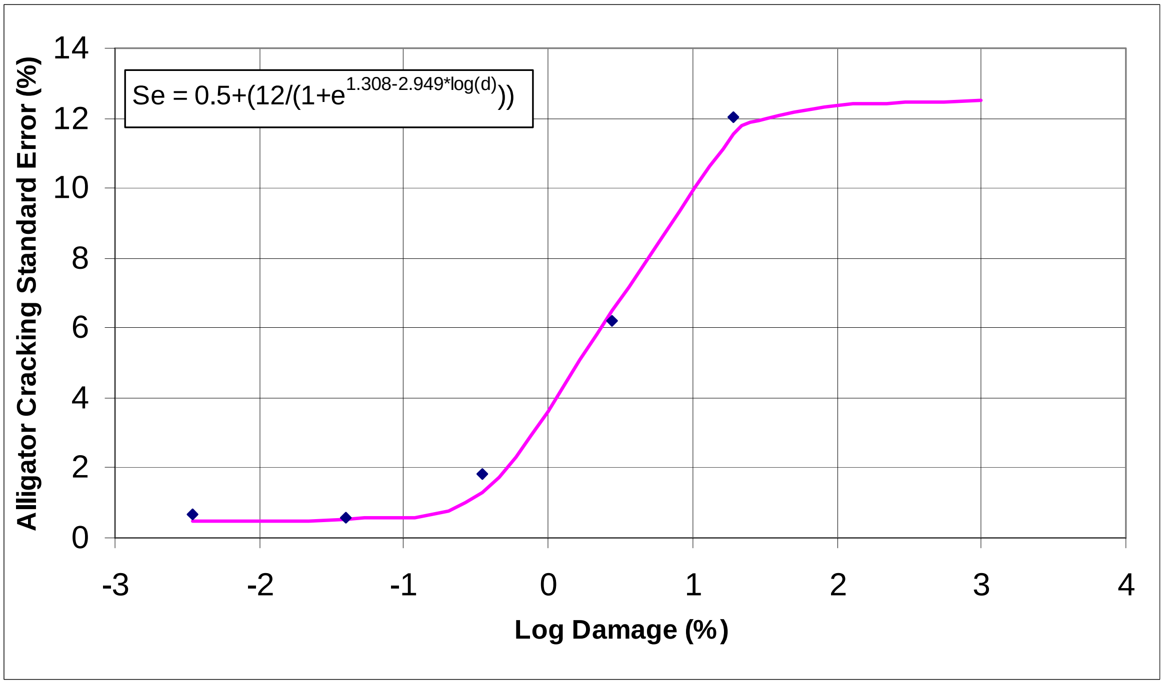

Figure 19. Standard error of estimate model for AC fatigue cracking

In this case, the standard error of estimate includes all sources of variation related to the prediction, including, at least, the following:

- Errors associated to material characterization parameters assumed or measured for design.
- Errors related to assumed traffic and environmental conditions during the design period.
- Model errors associated with the cracking prediction algorithms and corresponding calibration data used.

Step 4. Reliability analysis

Equation 7 allows performing the reliability analysis for predicted flexible pavement bottom up fatigue cracking. The approach is based on the results of the calibration and the deterministic analysis for fatigue cracking, assumed to be the expected average value for the distress. The reliability analysis involves the following steps:

3. Using the 2002 Design Guide bottom up fatigue cracking model for AC materials, predict the cracking level over the design period using mean inputs to the analysis system.

4. Estimate, for each month of the analysis period, the fatigue cracking threshold value for the desired reliability level using the following relationship:

$$Crack^{R}_{BottomUp} = \overline{Crack}_{BottomUp} + Se_{FC} * Z_R \qquad (8)$$

where

$Crack^{R}_{BottomUp}$ = cracking level corresponding to the reliability level R. It is expected that no more than (100-R)% of sections under similar conditions will have a fatigue cracking above $Crack^{R}_{BottomUp}$.

$\overline{Crack}_{BottomUp}$ = expected fatigue cracking estimated using the deterministic model with average input values for all parameters (corresponds to a 50 percent reliability level).

Se_{FC} = standard error of estimate obtained from calibration of the analysis system

Z_R = standard normal deviate (mean 0 and standard deviation 1) for the selected reliability level R.

If computed $Crack^{R}_{BottomUp}$ R is greater than 100 percent then the value of 100 percent is assumed.

Figure 20 show predicted fatigue cracking for different reliability levels for the LTPP sections 124135. One can see that an increase in the desired reliability level leads to an increase in the predicted reliability threshold value for fatigue cracking, consequently reducing the pavement life for a selected maximum acceptable limit for the distress.

If a pavement designer requires a 90 percent reliability for AC fatigue cracking, then the predicted 90 percent curve must not exceed some preselected critical value of cracking. This level should be selected by the designer prior to conducting the pavement design.

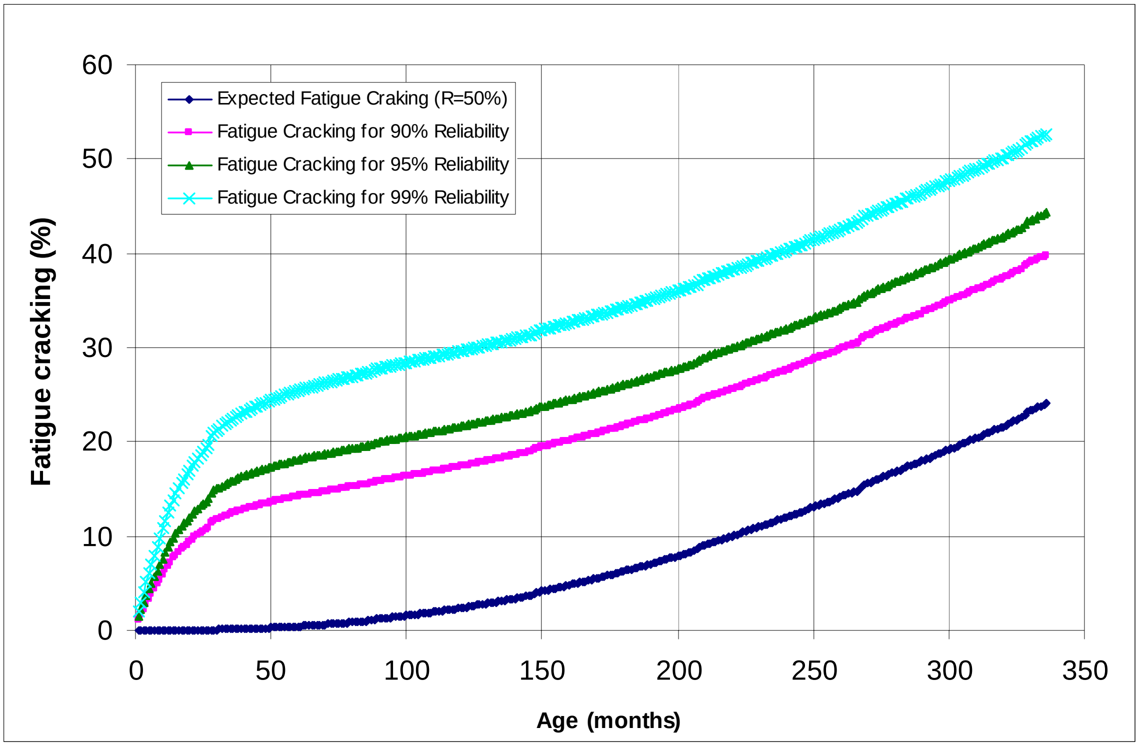

Figure 20. Predicted AC fatigue cracking for LTPP section 124135.

For example, considering Figure 20.

> Expected AC fatigue cracking at 50% reliability = 13 percent at 250 months.
> Estimated AC fatigue cracking for 90% reliability = 28 percent at 250 months.

Thus, a designer may state with 90 percent confidence that the designed pavement will present less than 28 percent of fatigue cracking at the end of the 250 month design life. This design is not adequate if the criteria established was a maximum cracking of 20% but it would be adequate if the criteria was 30% maximum cracking. Thus, for the first case the design must be altered so that the expected cracking is lower which will reduce each of the other curves until the design meets the performance criteria.

DESIGN RELIABILITY FOR AC LONGITUDINAL (TOP DOWN) CRACKING

The information presented in this section is applicable for new as well as rehabilitated flexible and semi-rigid pavement structures.

Introduction

The definition of reliability for AC longitudinal cracking for a given project under design is as follows:

R = P [Longitudinal Cracking of Design Project < Critical Level of Longitudinal Cracking Over Design Life]

where:

R is the reliability level
P is the probability

The expected (average) longitudinal cracking in ft/mile of the design project over time is assumed to depend on the tensile strains at the surface of the asphalt layers and, consequently, on all conditions affecting this pavement response. Longitudinal cracking is a stochastic or probabilistic variable whose prediction is uncertain. For example, if 100 projects were designed and built with the same design and specifications, they would ultimately exhibit a wide range of longitudinal cracking over time.

Average AC longitudinal cracking between similar projects follows a certain probability distribution. It was assumed that the expected longitudinal cracking is approximately normally distributed on the higher (greater than mean) side of the probability distribution (not on the lower side, particularly near zero cracking). Thus, the likely variation of cracking around the expected level estimated can be defined by the mean of the prediction model (at any time over the design life) and a standard deviation. The standard deviation is a function of the error associated with the predicted cracking and the data used to calibrate the fatigue cracking (bottom up) model.

This part summarizes the development of the reliability approach for flexible pavement longitudinal cracking based on the normal distribution assumption. This procedure is based on analysis of the predicted versus measured cracking (see Figure 21) and estimation of parameters of the corresponding error distribution.

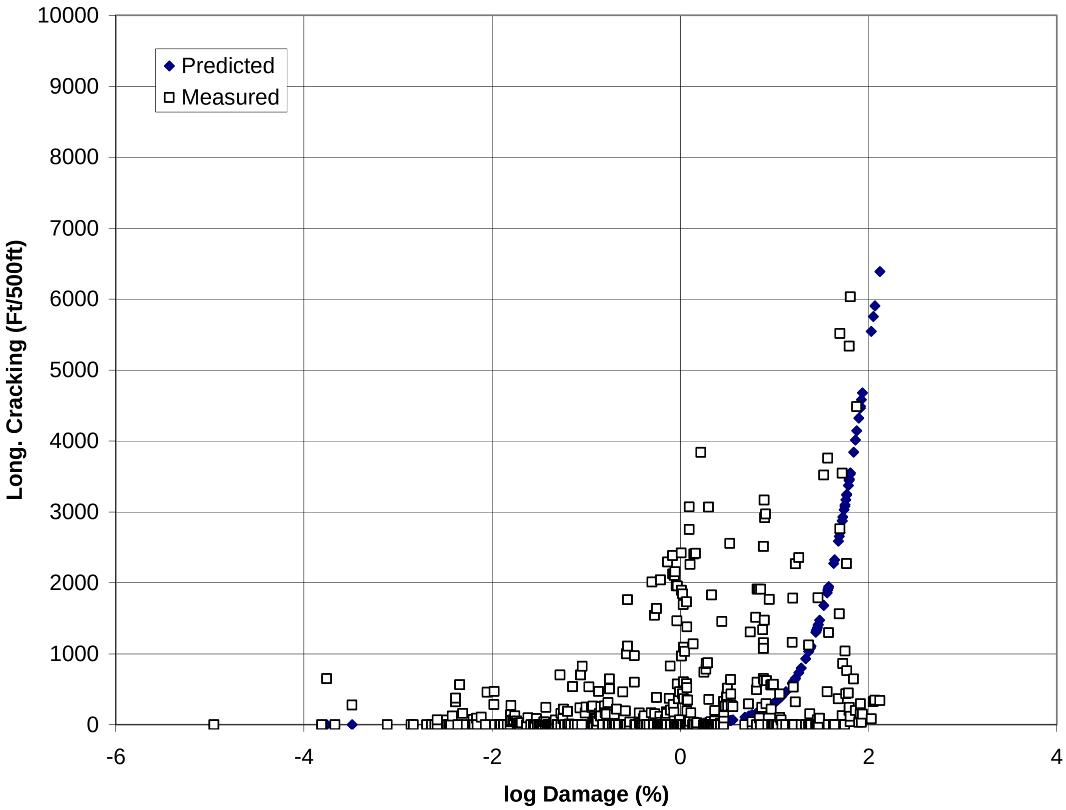

Figure 21. Predicted versus. measured asphalt concrete longitudinal cracking.

Step-by-Step Approach to Derive Parameters of the Error Distribution

Step 1 – Group all data points by the level of predicted cracking

All data points in the calibration database were divided into subgroups based on the level of predicted cracking. Table 9 shows the groups established after inspecting the data plots with residual (predicted – measured) on the y-axis versus predicted cracking on the x-axis (not shown here):

Table 9. Definition of groups for AC longitudinal cracking data.

Group	Range of Predicted log(Damage(%))	Number of Data Points
1	< -2	33
2	-2 to -1	69
3	-1 to 0	118
4	0 to 1	125
5	> 1	69

Step 2. Compute descriptive statistics for each group of data

For each predicted cracking group the following parameters were computed:

1. Predicted longitudinal cracking damage (each section and group average).
2. Predicted longitudinal cracking (each section).
3. Measured longitudinal cracking (each section).
4. Standard error of estimate for longitudinal cracking (each group).

Table 10 presents the summary results of this analysis.

Table 10. Computed statistical parameters for each data group (longitudinal cracking).

Group	Average Predicted log(Damage(%))	Standard Error for Predicted Longitudinal Cracking, ft/mi
1	-2.65476	204.83
2	-1.4756	200.158
3	-0.41277	702.8633
4	0.427707	1104.719
5	1.561249	2497.457

Step 3. Determine relationship for the standard error of estimate for longitudinal cracking.

Based on data from Table 10, the following relationship was developed (Figure 22):

$$Se_{LC} = 200+2300/(1+e^{1.07-2.165*\log D}) \quad (9)$$

where

Se_{LC} = standard error of estimate for longitudinal cracking
D = predicted longitudinal cracking damage (%)
R^2 = 88.7%
N = 5

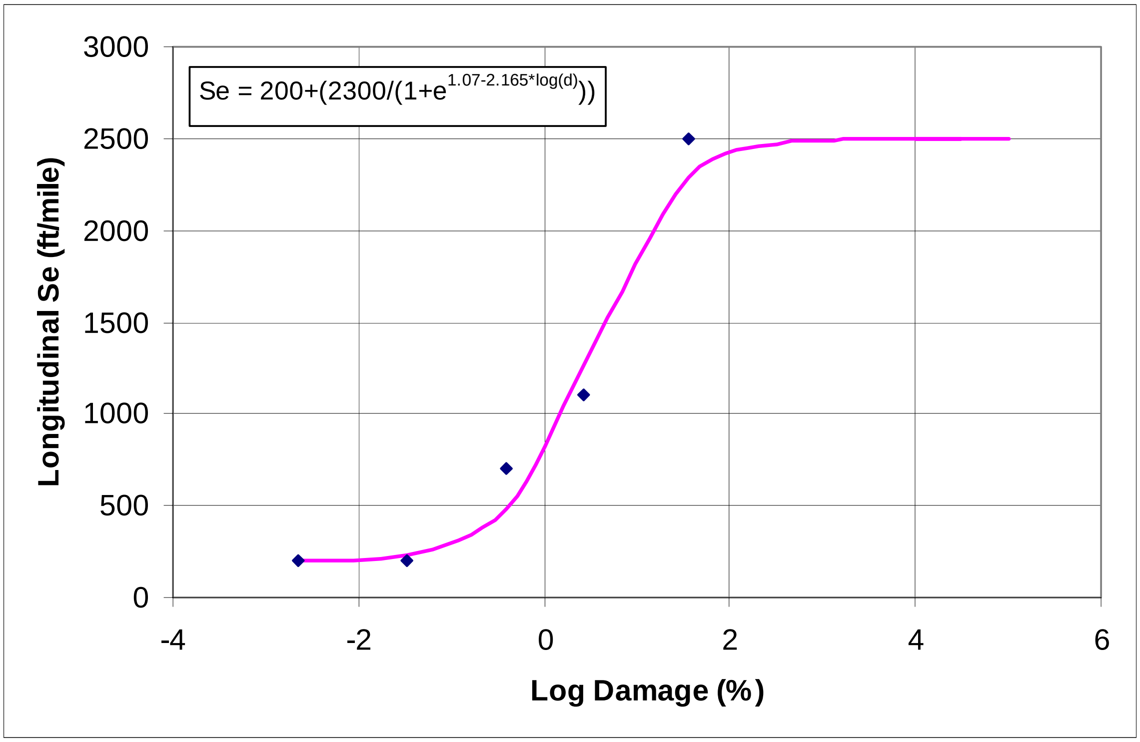

Figure 22. Standard error of estimate model for AC longitudinal cracking

In this case, the standard error of estimate includes all sources of variation related to the prediction, including, at least, the following:

- Errors associated to material characterization parameters assumed or measured for design.
- Errors related to assumed traffic and environmental conditions during the design period.
- Model errors associated with the cracking prediction algorithms and corresponding calibration data used.

Step 4. Reliability analysis

Equation 8 allows performing the reliability analysis for predicted flexible pavement top down longitudinal cracking. The approach is based on the results of the calibration and the deterministic analysis for longitudinal cracking, assumed to be the expected average value for the distress. The reliability analysis involves the following steps:

5. Using the 2002 Design Guide top down longitudinal cracking model for AC materials, predict the cracking level over the design period using mean inputs to the analysis system.

6. Estimate, for each month of the analysis period, the longitudinal cracking threshold value for the desired reliability level using the following relationship:

$$Crack^{R}_{TopDown} = \overline{Crack}_{TopDown} + Se_{LC} * Z_{R} \qquad (10)$$

where

$Crack^{R}_{TopDown}$ = cracking level corresponding to the reliability level R. It is expected that no more than (100-R)% of sections under similar conditions will have longitudinal cracking level above $Crack^{R}_{TopDown}$.

$\overline{Crack}_{TopDown}$ = expected cracking estimated using the deterministic model with average input values for all parameters (corresponds to a 50 percent reliability level).

Se_{LC} = standard error of estimate obtained for calibration of the analysis system

Z_R = standard normal deviate (mean 0 and standard deviation 1) for the selected reliability level R.

If computed $Crack^{R}_{TopDown}$ is greater than 100 percent then the value of 100 percent is assumed.

Figure 23 shows predicted longitudinal cracking for different reliability levels for the LTPP section 134112. One can see that an increase in the desired reliability level leads to an increase in the predicted reliability threshold value for longitudinal cracking, consequently reducing the pavement life for a selected maximum acceptable limit for the distress.

If a pavement designer requires a 90 percent reliability for AC longitudinal cracking, then the predicted 90 percent curve must not exceed some preselected critical value of cracking. The default critical value for longitudinal cracking is 1000 ft/mi in the 2002 Design Guide The user defined level should be selected by the designer prior to conducting the pavement design.

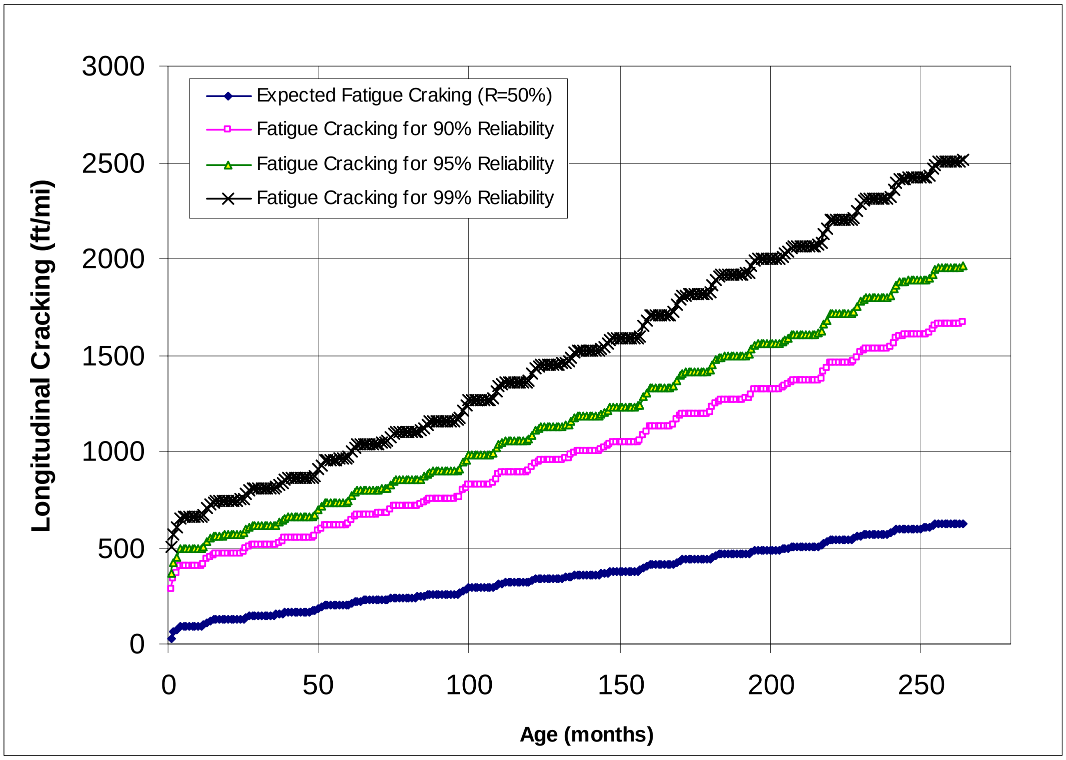

Figure 23. Predicted AC longitudinal cracking for LTPP section 134112.

For example, considering Figure 23.

Expected AC longitudinal cracking at 50% reliability = 600 ft/mile at 260 months.
Estimated AC longitudinal cracking for 90% reliability = 1700 ft/file at 260 months.

Thus, a designer may state with 90 percent confidence that the designed pavement will present less than 1700 ft/mile of longitudinal cracking at the end of the 260 month design life. If the threshold criteria is 1000 ft/mi, this design is not adequate. Thus, the design must be altered so that the expected cracking is lower which will reduce each of the other curves until the design meets the performance criteria.

DESIGN RELIABILITY FOR RUTTING IN FLEXIBLE PAVEMENTS

The information presented in this section is applicable for new as well as rehabilitated flexible and semi-rigid pavement structures, and for total rutting or rutting only in the asphalt layers of the pavement system.

Introduction

The definition of reliability for rutting in a given project under design is as follows:

R = P [Rutting of Design Project < Critical Rutting Over Design Life]

where:

R is the reliability level
P is the probability

The expected (average) maximum rutting in inches of the design project over time is assumed to depend on the vertical compressive strains causing permanent deformation in each layer of the pavement system and, consequently, on all conditions affecting this pavement response.
The 2002 Design Guide allows the user to conduct a reliability analysis either on the rutting caused by permanent deformation of asphalt concrete only, on the total pavement rutting or on both alternatives:

AC Rutting

$$ACRutting = \sum_{i=1}^{nac} ACPD_i \qquad (11)$$

where:

ACRutting = total rutting in asphalt layers only
$ACPD_i$ = permanent deformation in AC layer i
nac = total number of asphalt layers

Total Pavement Rutting

$$TotalRutting = \sum_{i=1}^{n} PD_i \qquad (12)$$

where:

TotalRutting = total pavement rutting
PD_i = permanent deformation in layer i
n = total number of pavement layers

It is also assumed that no or very small permanent deformation occurs in cement treated, PCC and bedrock materials, so that it may be neglected. Rutting is a stochastic or probabilistic variable whose prediction is uncertain. For example, if 100 projects were designed and built with the same design and specifications, they would ultimately exhibit a wide range of rutting over time.

Average permanent deformation between similar projects follows a certain probability distribution. It was assumed that the expected permanent deformation and consequently rutting is approximately normally distributed on the higher (greater than mean) side of the probability distribution. Thus, the likely variation of rutting around the expected level estimated can be defined by the mean of the prediction model (at any time over the design life) and a standard deviation. The standard deviation is a function of the error associated with the predicted rutting and the data used to calibrate the permanent deformation models for the various materials.

This part summarizes the development of the reliability approach for flexible pavement rutting based on the normal distribution assumption. This procedure is based on analysis of the predicted versus measured rutting for each type of material (see Figures 24, 25 and 26) and estimation of parameters of the corresponding error distributions.

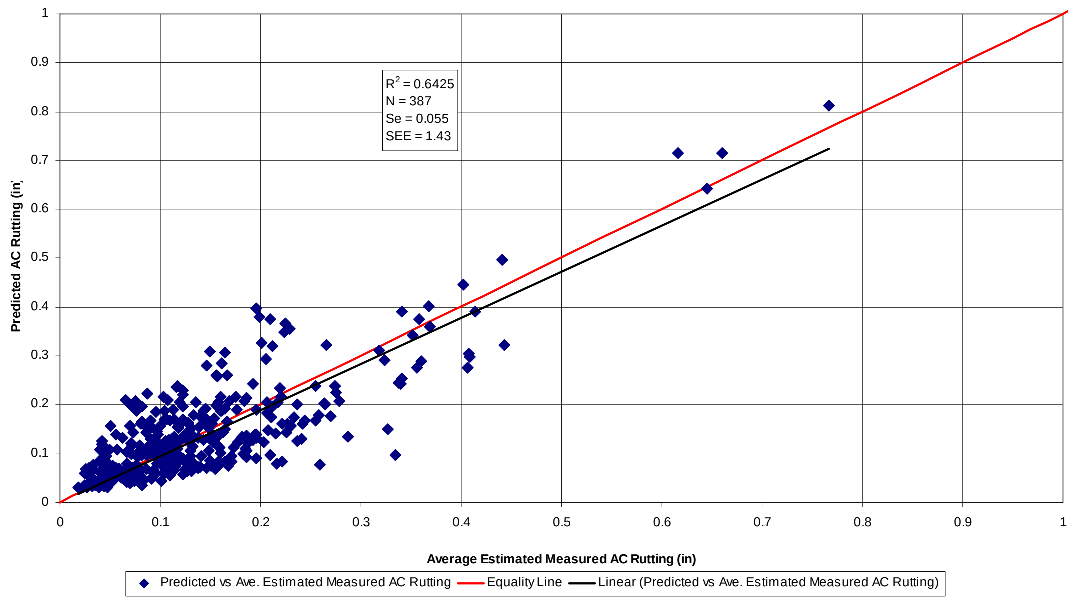

Figure 24. Nationally calibrated predicted versus estimated measured asphalt rutting..

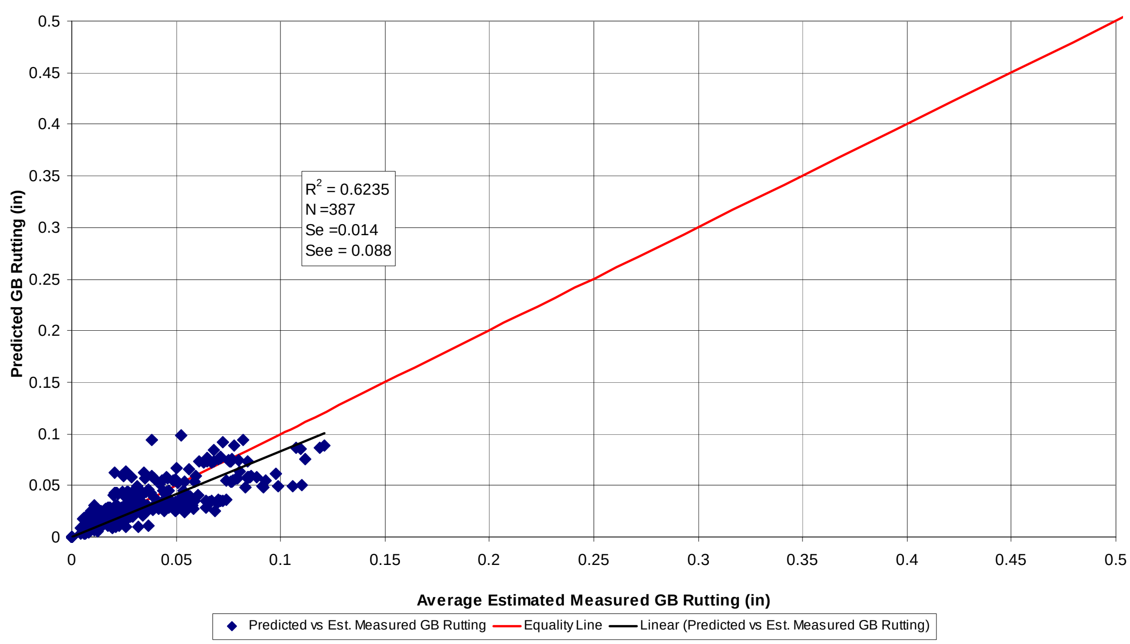

Figure 25. National calibrated predicted versus estimated measured granular base rutting.

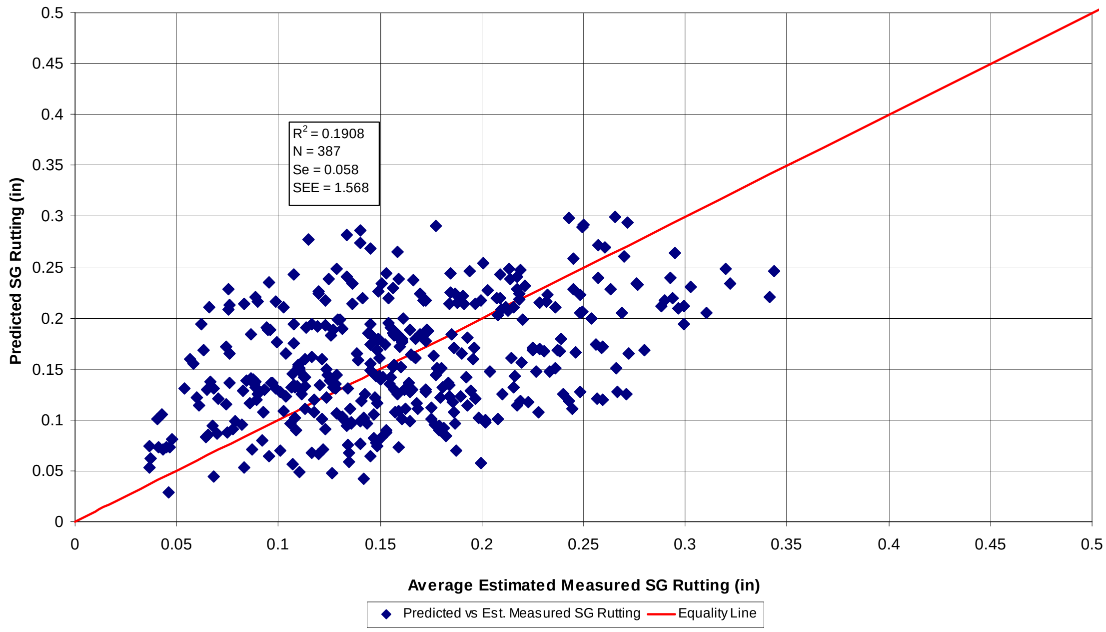

Figure 26. National calibrated predicted versus measured subgrade rutting.

Step-by-Step Approach to Derive Parameters of the Error Distribution

Step 1 – Group all data points by the level of predicted permanent deformation

All data points in the calibration database were divided into subgroups based on the level of predicted permanent deformation. Tables 11, 12 and 13 show the groups established for each type of material (AC, granular base and subgrade) after inspecting the data plots with residual (predicted – measured) on the y-axis versus predicted cracking on the x-axis:

Table 11. Definition of groups for AC permanent deformation data.

Group	Range of predicted AC rutting, inches	Number of data points
1	0 - 0.1	219
2	0.1 - 0.2	153
3	0.2 - 0.3	61
4	0.3 - 0.4	20
5	0.4 - 0.5	11
6	0.5 and above	6

Table 12. Definition of groups for granular base permanent deformation data.

Group	Range of predicted Base rutting, inches	Number of data points
1	0 - 0.05	294

2	0.05 - 0.1	115
3	0.1 - 0.15	41
4	0.15 - 0.2	20

Table 13. Definition of groups for subgrade permanent deformation data.

Group	**Range of predicted Subgrade rutting, inches**	**Number of data points**
1	0-0.05	105
2	0.05-0.1	155
3	0.1-0.15	148
4	0.15-0.2	36
5	0.2-0.25	19
6	0.25-0.4	7

Step 2. Compute descriptive statistics for each group of data

For each group of AC rutting data the following parameters were computed:

1. Expected (predicted) AC rutting.
2. Existing AC rutting (average).
2. Standard error of estimate for AC rutting.

These parameters are presented in Tables 14, 15 and 16 and plotted in Figures 31, 32 and 33, respectively.

Table 14. Computed statistical parameters for each data group (AC permanent rutting).

Group	**Average Predicted AC Rutting, inches**	**Average Measured AC Rutting, inches**	**Standard Error for Predicted AC Rutting, inches**
1	0.0457	0.0597	0.0337
2	0.1438	0.1465	0.0627
3	0.2392	0.1196	0.0883
4	0.3465	0.2998	0.1272
5	0.4342	0.3186	0.1498
6	0.7356	0.6711	0.0853

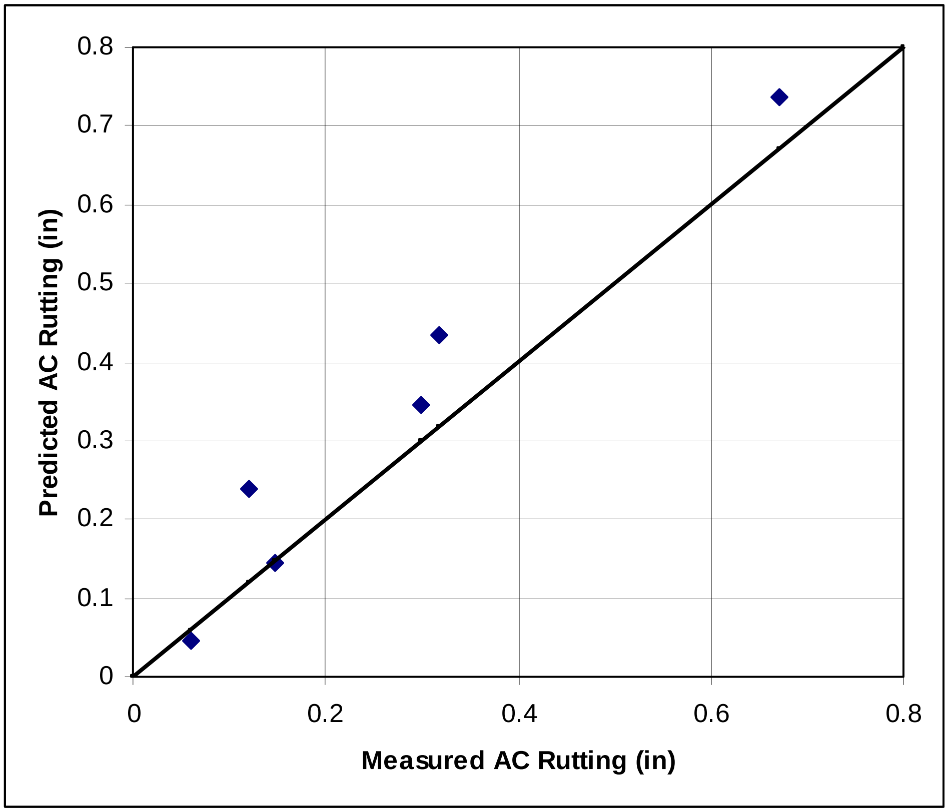

Figure 27. Average predicted vs. measured AC permanent deformation for each group of data.

Table 15. Computed statistical parameters for each data group (granular base rutting).

Group	Average Predicted Granular Base Rutting, inches	Average Measured Granular Base Rutting, inches	Standard Error for Predicted Granular Base Rutting, inches
1	0.0177	0.0205	0.0138
2	0.0700	0.0732	0.0301
3	0.1282	0.1178	0.0320
4	0.1593	0.1275	0.0514

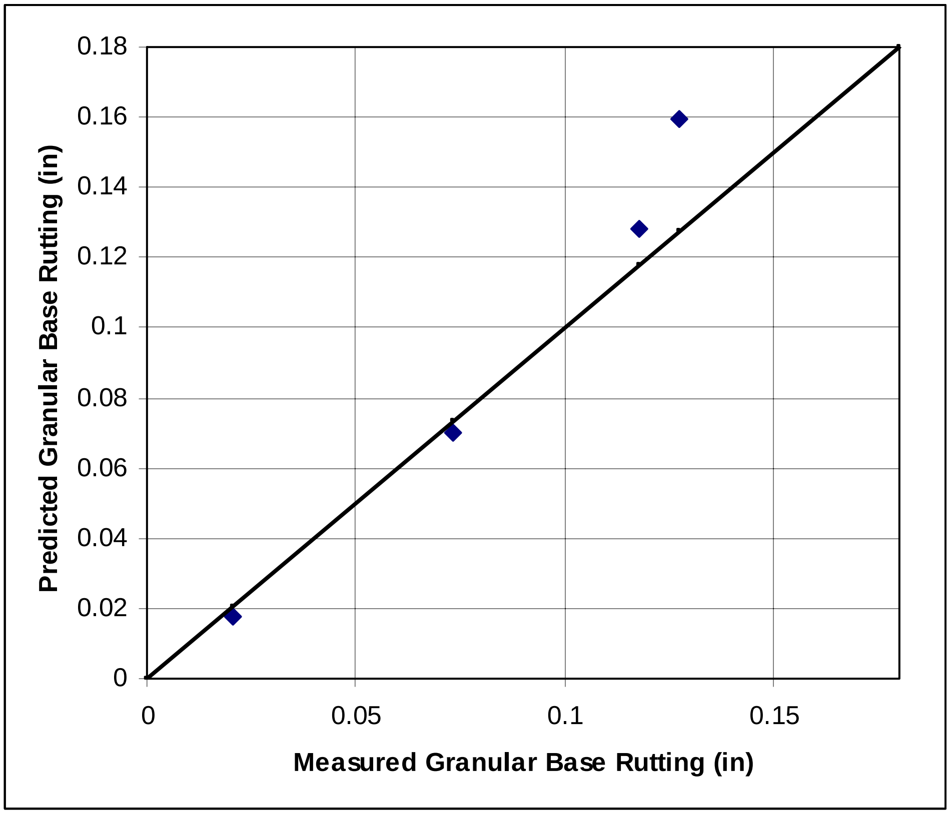

Figure 28. Average predicted vs. measured granular base permanent deformation for each group of data.

Table 16. Computed statistical parameters for each data group (subgrade t rutting).

Group	Average Predicted Subgrade Rutting, inches	Average Measured Subgrade Rutting, inches	Standard Error for Predicted Subgrade Rutting, inches
1	0.0087	0.0116	0.0130
2	0.0784	0.0893	0.0419
3	0.1209	0.1332	0.0447
4	0.1709	0.1437	0.0656
5	0.2121	0.1337	0.0878
6	0.3267	0.2464	0.0906

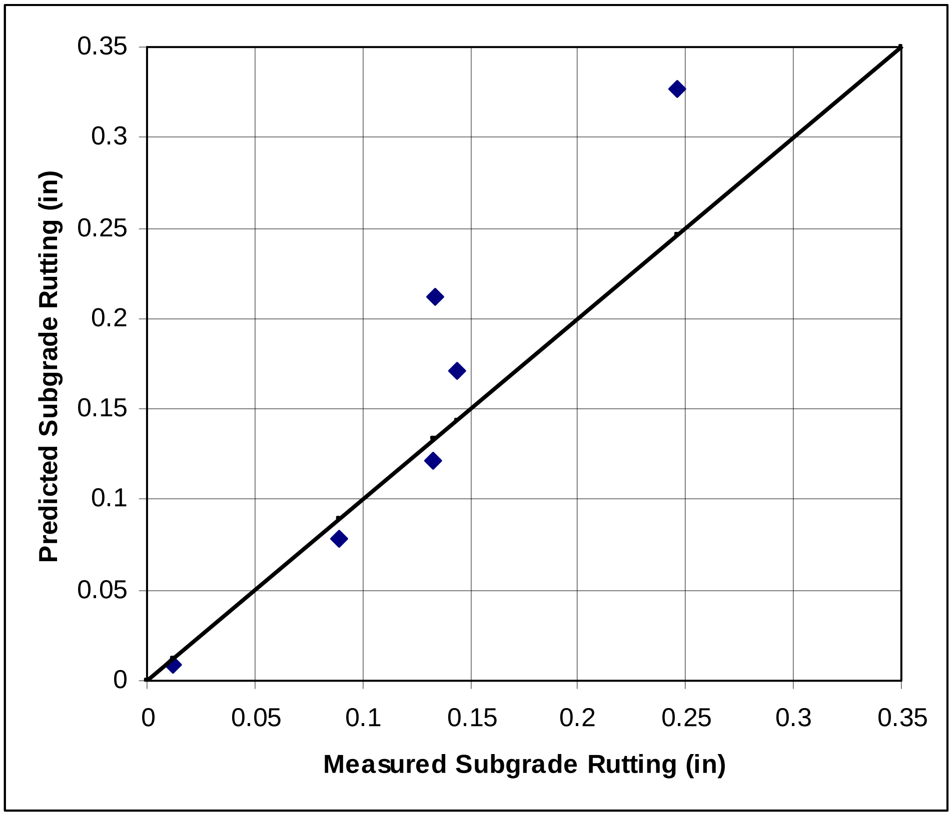

Figure 29. Average predicted vs. measured subgrade permanent deformation for each group of data.

Step 3. Determine relationship for the standard error of estimate for AC, Granular Base and Subgrade Rutting.

Based on above data, the following relationships were developed (Figures 30, 31 and 32):

Asphalt Concrete Materials

$$STD_{PDAC} = 0.1587\ PD_{ac}^{0.4579} \tag{13}$$

where

Se_{PDAC} = standard error for AC permanent deformation from calibration
PD_{AC} = predicted AC permanent deformation, inches
R^2 = 69.8%
N = 6

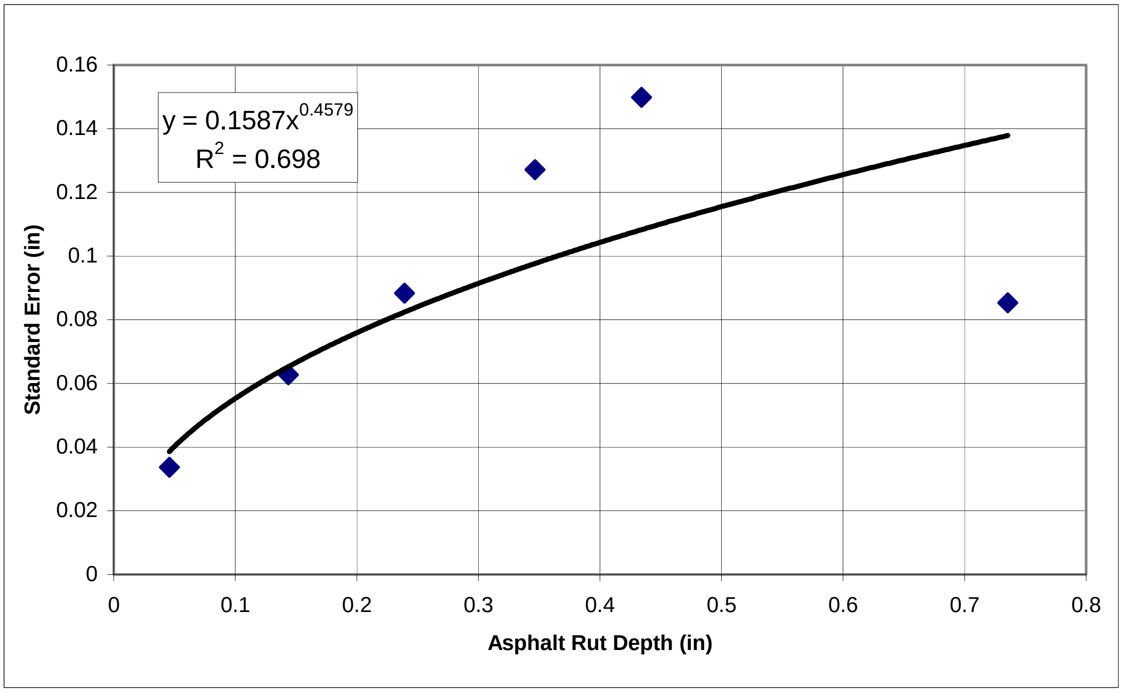

Figure 30. Standard error of estimate model for AC permanent deformation

Base Materials

$$Se_{PDGB} = 0.1169\ PD_{GB}^{0.6303} \quad (14)$$

where

Se_{PDGB} = standard error for granular base permanent deformation
PD_{GB} = predicted granular base permanent deformation, inches
R^2 = 92.3%
N = 4

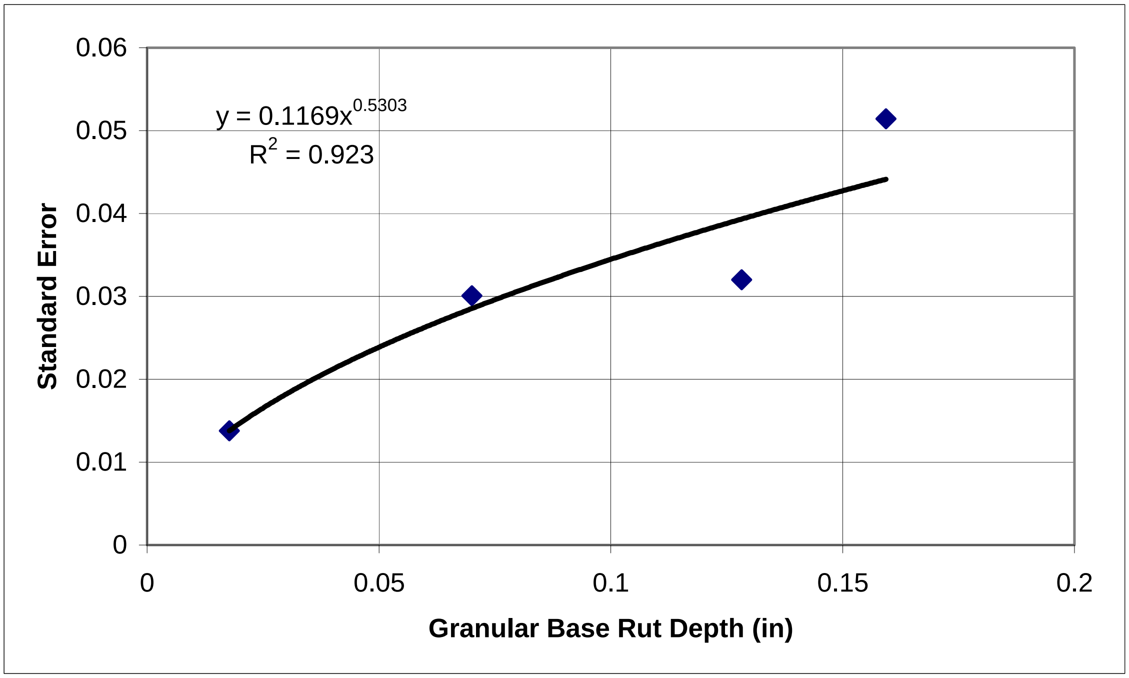

Figure 31. Standard error of estimate model for granular base permanent deformation

Subgrade

$$Se_{PDSG} = 0.1724\ PD_{SG}^{0.5516} \qquad (15)$$

where

Se_{PDSG} = standard error for subgrade permanent deformation
PD_{SG} = predicted subgrade permanent deformation, inches
R^2 = 97.4%
N = 6

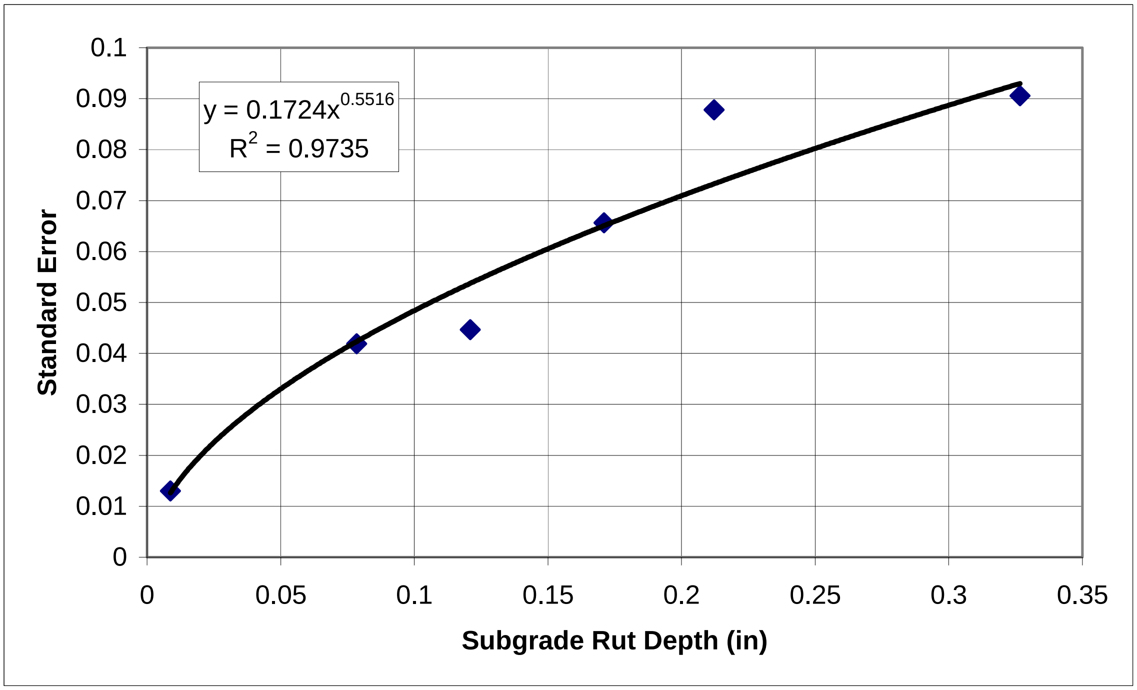

Figure 32. Standard error of estimate model for subgrade permanent deformation

In the three cases, the standard error of estimate includes all sources of variation related to the prediction of permanent deformation for each type of material, including, at least, the following:

- Errors associated to material characterization parameters assumed or measured for design.
- Errors related to assumed traffic and environmental conditions during the design period.
- Model errors associated with the permanent deformation prediction algorithms and corresponding calibration data used.

Step 4. Reliability analysis

The 2002 Design Guide allows the user performing the reliability analysis for both asphalt concrete and/or total pavement rutting. The approach is based on the results of the calibration and the deterministic analysis for permanent deformation, assumed to be the expected average value for the distress. The reliability analysis involves the following steps:

1. Use the 2002 Design Guide system and average input data for the parameters to estimate the expected permanent deformation in all layers and the subgrade for every month of the analysis period.

2. Compute, for each month, the expected total AC rutting and total pavement rutting using equations (11) and (12) respectively.

3. Estimate, for each month of the analysis period, the AC rutting and/or total rutting threshold value for the desired reliability level using the following relationships:

$$\mathrm{Rutting}_{AC}^{R} = \overline{\mathrm{Rutting}}_{AC} + \mathrm{Se}_{AC} * Z_R \tag{16}$$

$$\mathrm{Rutting}_{Total}^{R} = \overline{\mathrm{Rutting}}_{Total} + \mathrm{Se}_{Total} * Z_R \tag{17}$$

$$\mathrm{Se}_{TR} = \sqrt{(\mathrm{Se}_{PDAC})^2 + (\mathrm{Se}_{PDGB})^2 + (\mathrm{Se}_{PDSG})^2} \tag{18}$$

where

$\mathrm{Rutting}_{AC}^{R}$	=	AC rutting corresponding to the reliability level R. It is expected that no more than (100-R)% of sections under similar conditions will have AC rutting above $\mathrm{Rutting}_{AC}^{R}$.
$\overline{\mathrm{Rutting}}_{AC}$	=	expected AC rutting (equation 10) estimated using the deterministic model with average input values for all parameters (corresponds to a 50 percent reliability level).
$\mathrm{Rutting}_{Total}^{R}$	=	Total pavement rutting corresponding to the reliability level R. It is expected that no more than (100-R)% of sections under similar conditions will have AC rutting above $\mathrm{Rutting}_{Total}^{R}$.
$\overline{\mathrm{Rutting}}_{Total}$	=	expected total rutting (equation 10) estimated using the deterministic model with average input values for all parameters (corresponds to a 50 percent reliability level).
Se_{TR}	=	standard error for the total rutting
Se_{PDAC}	=	standard error estimated for permanent deformation of AC layers computed from (13).
Se_{PDGB}	=	standard error estimated for permanent deformation of granular granular bases computed from (14).
Se_{PDSG}	=	standard error estimated for permanent deformation the subgrade computed from (15).
Z_R	=	standard normal deviate for the selected reliability level R.

Figures 33 and 34 show predicted total pavement rutting and AC rutting, respectively, for different reliability levels for the LTPP section 124106. One can see that an increase in the desired reliability level leads to an increase in the predicted reliability threshold value for rutting, consequently reducing the pavement life for a selected maximum acceptable limit for the distress.

If a pavement designer requires a 90 percent reliability for total rutting, then the predicted 90 percent curve must not exceed some preselected critical value of total rutting. This level should be selected by the designer prior to conducting the pavement design.

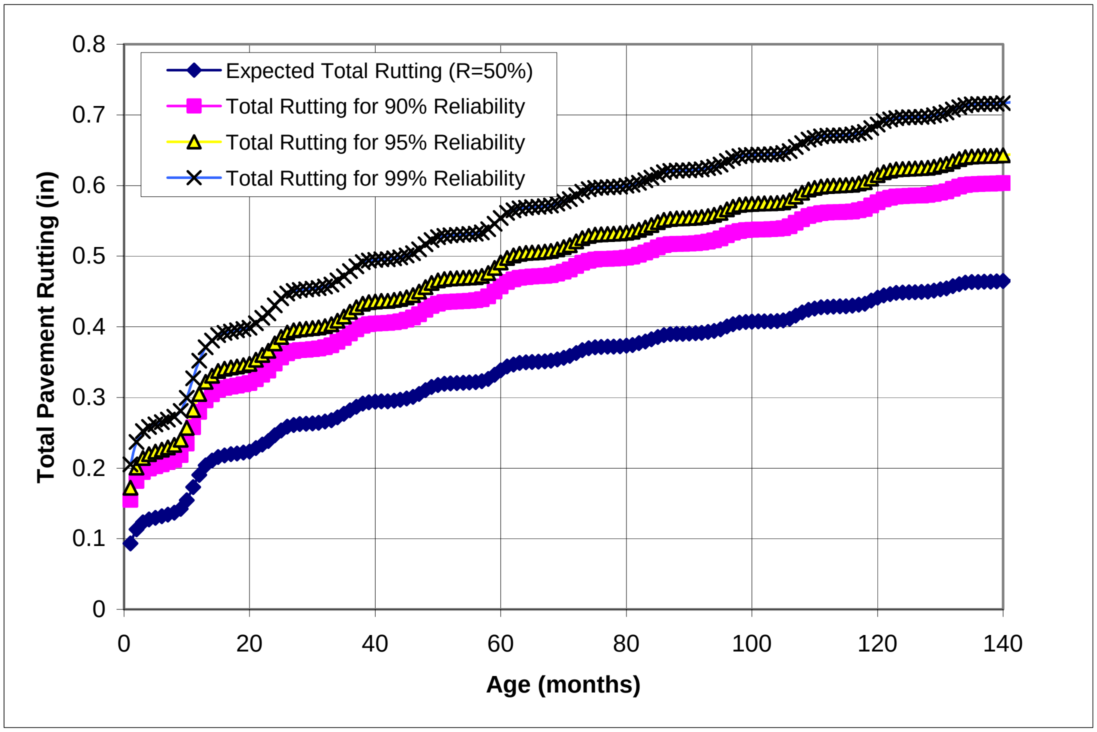

Figure 33. Predicted Total Rutting for LTPP section 124106.

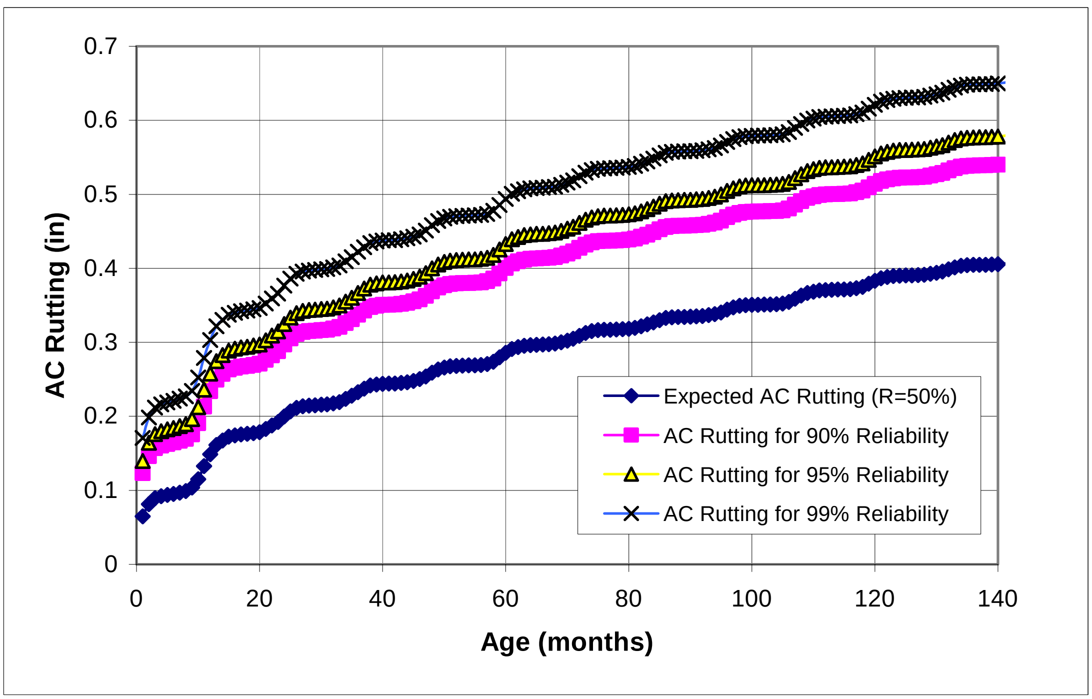

Figure 34. Predicted AC Rutting for LTPP section 124106.

For example, considering Figure 33.

Expected total rutting at 50% reliability = 0.44 inches at 120 months.
Estimated total rutting for 90% reliability = 0.58 inches at 120 months.

Thus, a designer may state with 90 percent confidence that the designed pavement will present less than 0.58 inches of total rutting at the end of the 120 month analysis period. But this design is not adequate for a criteria of 0.5 inches maximum allowable rutting. Thus, the design must be altered so that the expected rutting is lower than 0.5 inches at the 90% reliability level which will reduce each of the other curves until the design meets the performance criteria.

DESIGN RELIABILITY FOR AC THERMAL CRACKING

The information presented in this section is applicable for new as well as rehabilitated flexible and semi-rigid pavement structures.

Introduction

The definition of reliability for AC thermal cracking for a given project under design is as follows:

R = P [Thermal Cracking of Design Project < Critical Level of Thermal Cracking Over Design Life]

where:

R is the reliability level
P is the probability

The expected (average) thermal cracking in ft per 500 ft of pavement length over time is assumed to depend on material and environmental conditions. Thermal cracking is a stochastic or probabilistic variable whose prediction is uncertain. For example, if 100 projects were designed and built with the same design and specifications, they would ultimately exhibit a wide range of thermal cracking over time.

Average AC thermal cracking between similar projects follows a certain probability distribution. It was assumed that the expected percentage of thermal cracking is approximately normally distributed on the higher (greater than mean) side of the probability distribution (not on the lower side, particularly near zero cracking). Thus, the likely variation of cracking around the expected level estimated can be defined by the mean of the prediction model (at any time over the design life) and a standard deviation. The standard deviation is a function of the error associated with the predicted cracking and the data used to calibrate the thermal cracking model.

This part summarizes the development of the reliability approach for thermal cracking based on the normal distribution assumption. The procedure is based on the standard error of estimate found for each level of analysis during the calibration process. Figures 35 and 36 (level 1), 37 and 38 (level 2) and Figure 39 (level 3) show the predicted versus measured cracking from the calibration results.

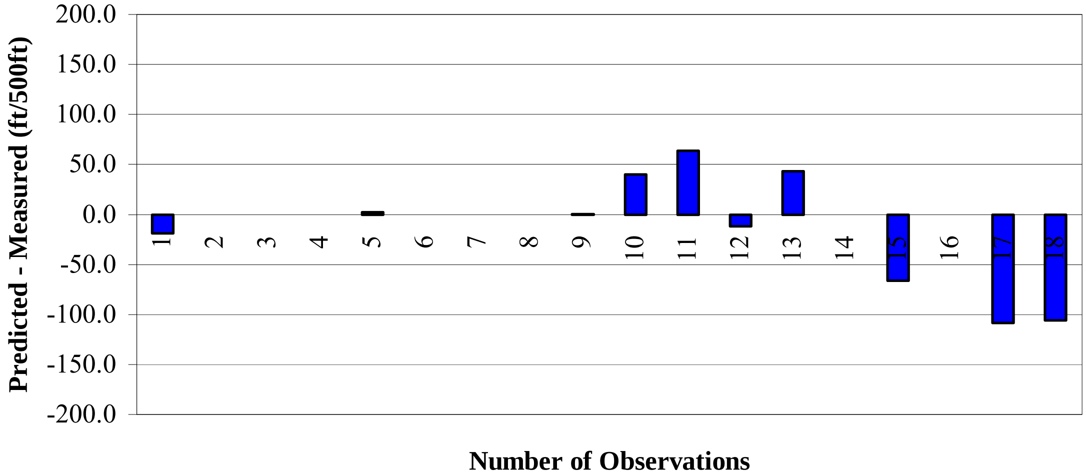

Figure 35. Level 1 Prediction Errors (Actual Pavement Temperature)

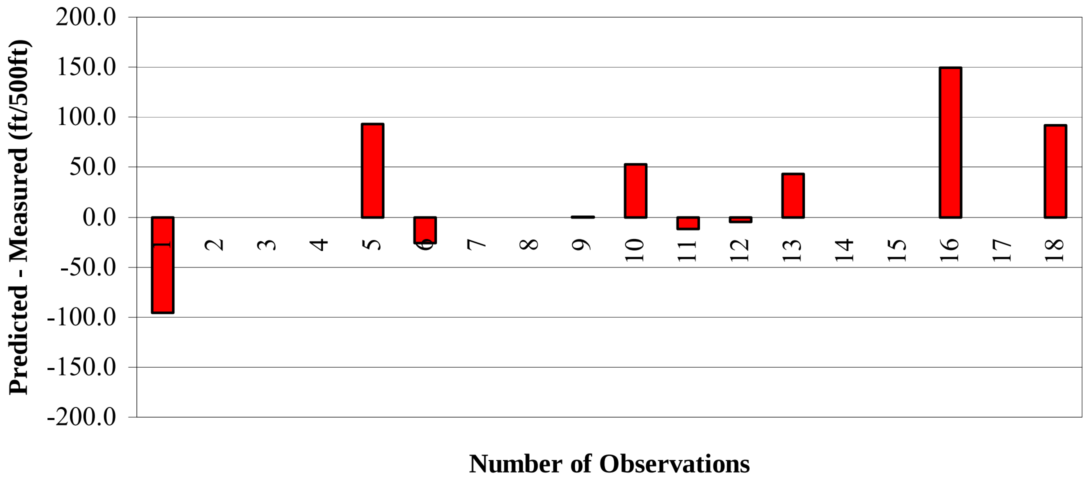

Figure 36. Level 1 Prediction Errors (Estimated Pavement Temperatures based on Historic Data)

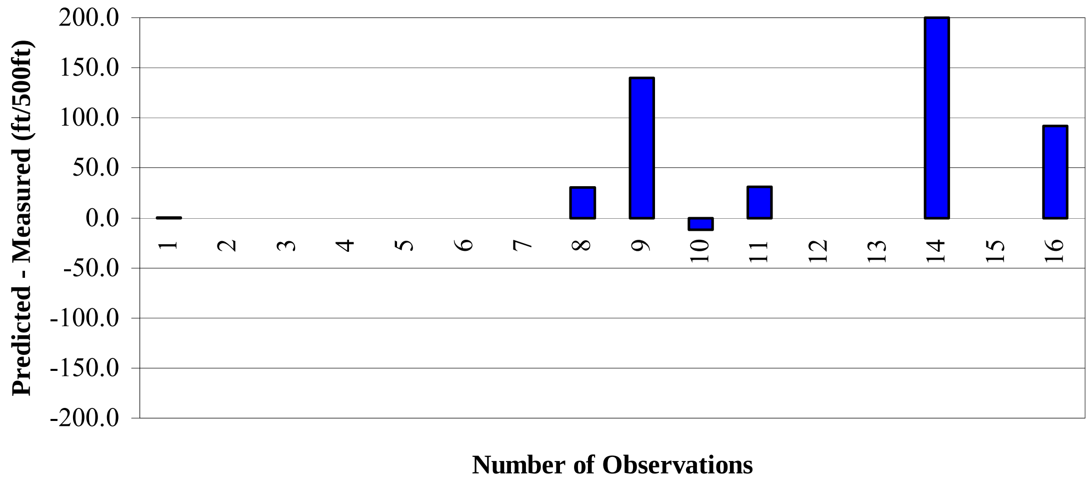

Figure 37. Level 2 Prediction Errors (Actual Pavement Temperature)

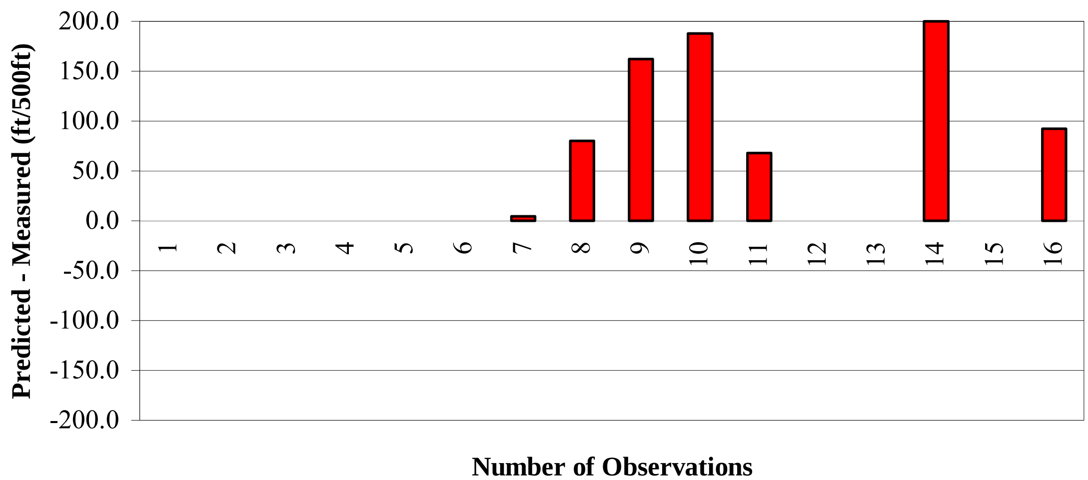

Figure 38. Level 2 Prediction Errors (Estimated Pavement Temperatures based on Historic Data)

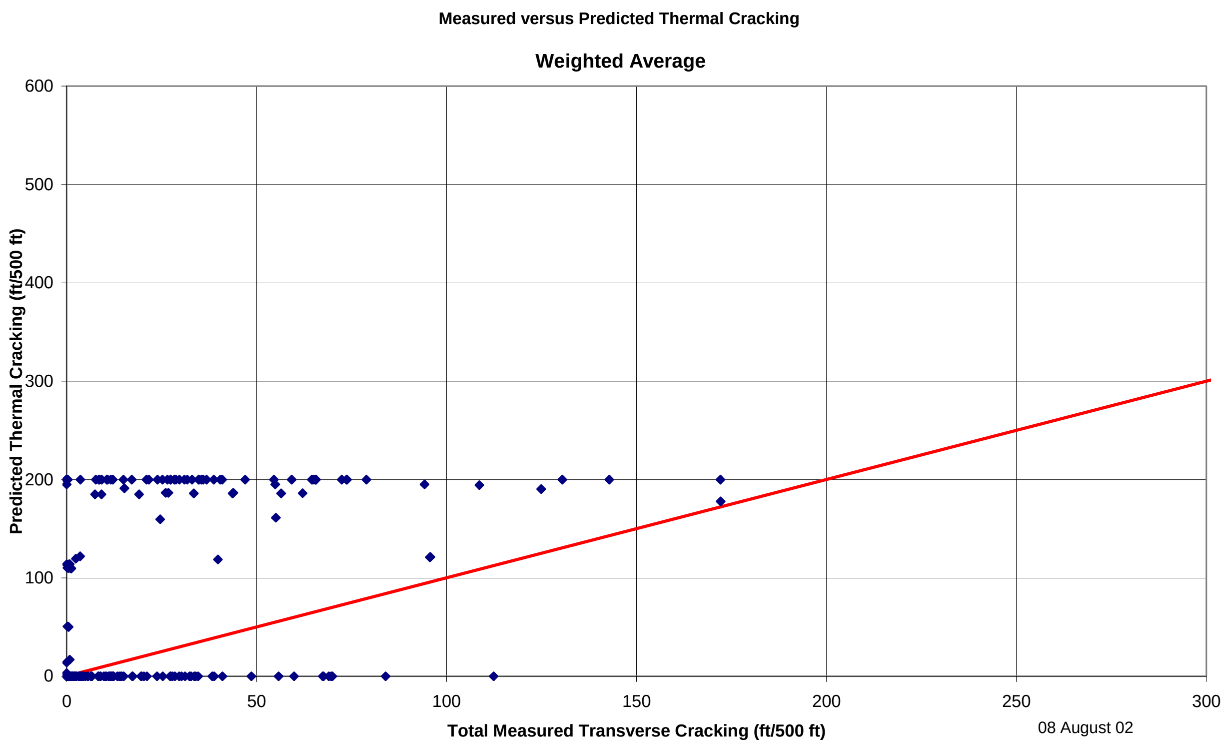

Figure 39. National calibrated predicted (level 3) versus measured thermal cracking

Standard Error of Estimate

All data points in the level 3 calibration database were divided into subgroups based on the level of predicted cracking. Table 17 shows the groups established after inspecting the data plots with residual (predicted – measured) on the y-axis versus predicted cracking on the x-axis (not shown here):

Table 17. Definition of groups for level 3 thermal cracking data.

Group	Range of predicted cracking, ft/500ft	Number of data points
1	0 – 4	56
2	4-114	14
3	114 - 196	25
4	196 - 200	61

Step 2. Compute descriptive statistics for each group of data

For each predicted cracking group the following parameters were computed:

1. Predicted thermal cracking (average).
2. Error (Predicted – Measured) for prediction of thermal cracking.
3. Standard error of estimate for thermal cracking (each group).

These parameters are presented in Table 8 and plotted in Figure 19.

Table 18. Statistical parameters for each data group (level 3 thermal cracking analysis).

Group	**Average Predicted Cracking, percent**	**Standard Error for Predicted Cracking, ft/500ft**
1	9.16E-02	26.1
2	8.43E+01	94.9
3	1.69E+02	133.2
4	2.00E+02	171.3

It should be noted that there was not enough data (low number of sections) for levels 1 and 2 analysis to develop the corresponding models for the standard error. In this case, the model for level 3 analysis was modified to yield estimated errors that are proportionally lower for levels 1 and 2. The ratio used was the one corresponding to the ratio of the overall standard error of estimate for the specific level of analysis compared to level 3 (Table 9).

Table 19. Assumed error ratios for levels 1 and 2 analysis.

Statistical Parameter	**Analysis Level**		
	1	**2**	**3**
Overall Standard Error	44.7	60.9	122.9
Ratio	0.364	0.495	1.0

Step 3. Determine relationship for the standard error of estimate for thermal cracking.

Based on data from Table 18 and the ratios from Table 19, for each level of analysis, the following relationships were developed (Figure 40):

Level 1: $Se_{TC\_1} = 0.2474 * THERMAL + 10.619$ (19a)

Level 2: $Se_{TC\_2} = 0.3371 * THERMAL + 14.468$ (19b)

Level 3: $Se_{TC\_3} = 0.6803 * THERMAL + 29.197$ (19c)

where

Se_{TC_i} = standard error of estimate for thermal cracking (ft/500ft) for level i analysis

THERMAL = predicted thermal cracking in ft/500ft
N = 4 (all levels)
R^2 = 97.9% (all levels)

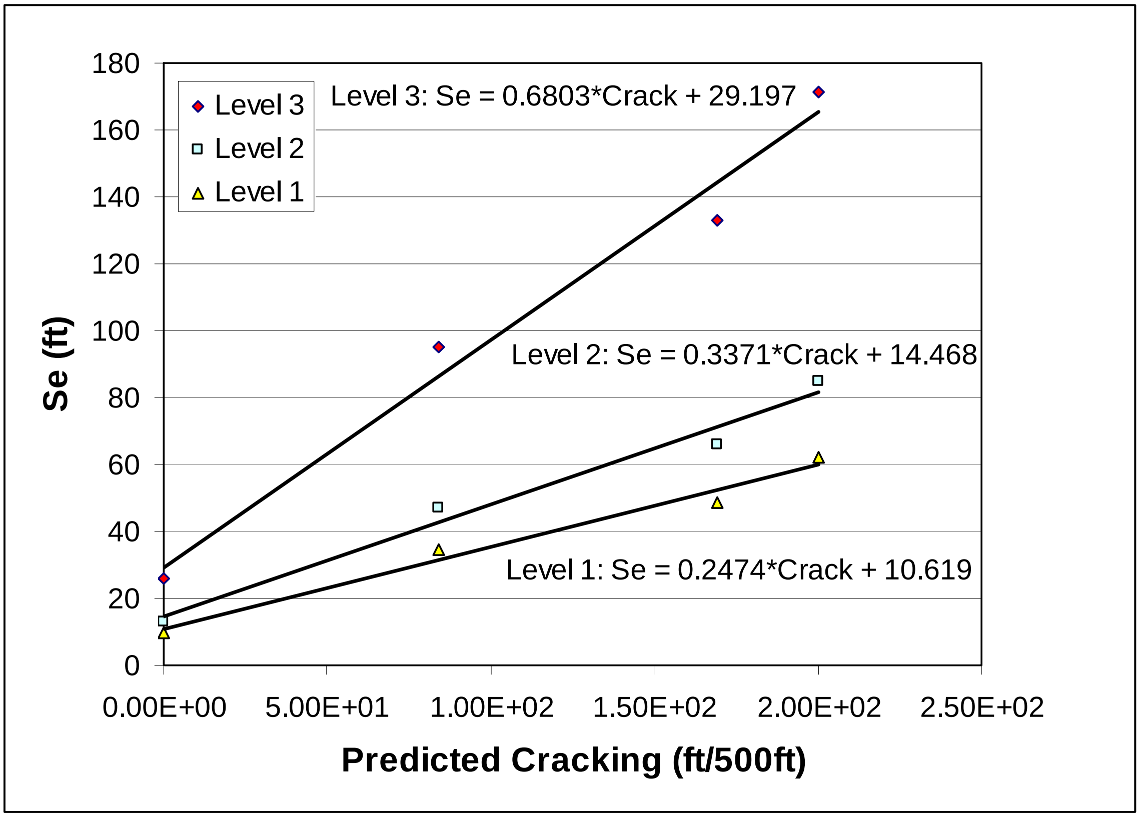

Figure 40. Standard error of estimate models for thermal cracking

In this case, the standard error of estimate includes all sources of variation related to the prediction, including, at least, the following:

- Errors associated to material characterization parameters assumed or measured for design.
- Errors related to assumed environmental conditions during the design period.
- Model errors associated with the cracking prediction algorithms and corresponding calibration data used.

<u>Step 4. Reliability analysis</u>

Equations 19 and 20 allow performing the reliability analysis for predicted flexible thermal cracking. The approach is based on the results of the calibration and the deterministic analysis for fatigue cracking, assumed to be the expected average value for the distress. The reliability analysis involves the following steps:

4. Using the 2002 Design Guide thermal cracking model for AC materials, predict the cracking level over the design period using mean inputs to the analysis system.

5. Estimate, for each month of the analysis period, the thermal cracking threshold value for the desired reliability level using the following relationship:

$$\mathrm{Crack}^{R}_{\mathrm{Thermal}} = \overline{\mathrm{Crack}}_{\mathrm{Thermal}} + \mathrm{Se}_{\mathrm{TC}} * Z_{R} \tag{20}$$

where

$\mathrm{Crack}^{R}_{\mathrm{Thermal}}$ = cracking level corresponding to the reliability level R. It is expected that no more than (100-R)% of sections under similar conditions will have thermal cracking level above $\mathrm{Crack}^{R}_{\mathrm{Thermal}}$.

$\overline{\mathrm{Crack}}_{\mathrm{Thermal}}$ = expected thermal cracking estimated using the deterministic model with average input values for all parameters (corresponds to a 50 percent reliability level).

Se_{TC} = standard error of estimate obtained for calibration of the analysis system, which depends upon the analysis level selected

Z_R = standard normal deviate (mean 0 and standard deviation 1) for the selected reliability level R.

If computed $\mathrm{Crack}^{R}_{\mathrm{Thermal}}$ is greater than 200ft per 500ft lane length, the value of 200 ft is assumed.

Figure 21 show predicted thermal cracking for different reliability levels for the LTPP section 011002. One can see that an increase in the desired reliability level leads to an increase in the predicted reliability threshold value for thermal cracking, consequently reducing the pavement life for a selected maximum acceptable limit for the distress.

If a pavement designer requires a 90 percent reliability for thermal cracking, then the predicted 90 percent curve must not exceed some preselected critical value of cracking. This level should be selected by the designer prior to conducting the pavement design.

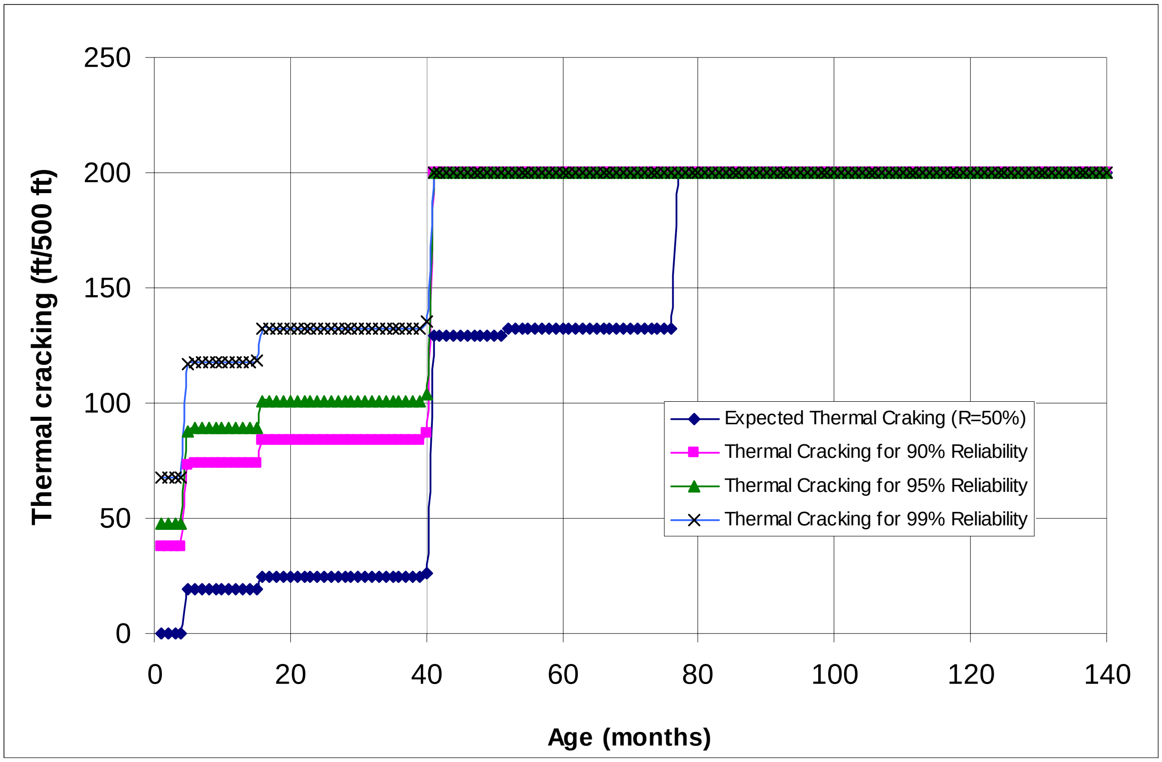

Figure 41. Predicted thermal cracking for LTPP section 011002.

For example, considering Figure 21.

> Expected thermal cracking at 50% reliability = 25 ft/500ft at 30 months.
> Estimated thermal cracking for 90% reliability = 84 ft/500ft at 30 months.
> Estimated thermal cracking for 99% reliability = 132 ft/500ft at 30 months.

Thus, a designer may state with 90 percent confidence that the designed pavement will present less than 84 ft/500ft of thermal cracking at the end of the 30 months. If a threshold criteria of 100ft/500ft was used, the designer could assume the pavement will last more than 30 months but it will fail beyond 40 months as the thermal cracking increases to 200ft/500ft for either level of reliability selected. This design is not adequate for that criteria. Thus, the design must be altered so that the expected cracking is lower which will reduce each of the other curves until the design meets the performance criteria.

DESIGN RELIABILITY FOR THE IRI MODELS

Introduction

Reliability analysis is a requirement in pavement design due to the stochastic nature of the inputs to the design as well as the predicted outputs from the design (e.g., pavement distress or smoothness). Several approaches can be adopted to perform reliability-based design, ranging from closed-form approaches to simulation-based methods; however, some methods may be more suitable than others given the complexities of the design procedure and the long computer run times required. In the 2002 Design Guide, considering the computational intensity of some of the deterministic design algorithms, and the computing power available at the present time, it was decided to pursue a closed-form approach for reliability design. A more sophisticated reliability approach can be considered within the implementation time frame of the Design Guide (expected to take 1 to 2 years) as computing power continues to improve exponentially.

A closed-form approach for reliability design based on model standard errors observed during the calibration process in Stage C of the project have been discussed in other similar memoranda. This memo summarizes the development of a reliability procedure for IRI prediction. The procedure for reliability estimation if IRI is based on a variance analysis of the IRI prediction models.

Definition of Reliability

The smothness of a design project over time, expressed in terms of the International Roughness Index (IRI), depends on many factors including:

- Initial as-constructed IRI.
- Development of pavement distresses.
- Maintenance activities.
- Foundation movements, e.g., swelling, settlement, frost heave, etc.

In developing regression models for predicting IRI, several of these factors are commonly considered as inputs. Given the stochastic nature of the inputs that enter the IRI prediction, it can easily be seen that the IRI estimate is also stochastic or probabilistic in nature. For example, if 100 projects were designed and constructed with the same design and specifications, they would ultimately over time exhibit a wide range of smoothness as measured by the IRI. Data from previous field studies shows that the coefficient of variation of mean smoothness (present serviceability rating) from project to project within a group of similar designs within a given state averaged 8 percent. ("Long-Term Pavement Performance Pre-Implementation Activities," technical report prepared for SHRP by J. B. Rauhut, M. I. Darter, R. L. Lytton, and R. E. DeVor, 1986.) The CV for the IRI may indeed be greater than this value but it is a starting point.

Within the context of the 2002 Design Guide, the reliability of a given design is the probability that the performance of the pavement predicted for that design will be satisfactory over the time period under consideration. Depending on user choice, design reliability can either be considered directly for each key distress type or using an overall measure of pavement performance (such as ride quality), or both. If pavement smoothness expressed in terms of IRI is the performance measure, the reliability of a pavement can be mathematically expressed as:

$$P[\ IRI(\text{Construction factors, pavement structural distress, site factors, model error})\ ] < IRI_{critical} \quad (7)$$

The probability that a trial design will satisfy the inequality in equation (7) defines its reliability.

Calibrated Models for IRI Prediction in Rigid Pavements

The following calibrated models were developed in Stage C for predicting IRI. It is important to understand the inputs that enter the IRI models and the associated model statistics (R^2 and SEE) in order to perform a variance analysis of the components for reliability estimation.

JPCP IRI Prediction

The JPCP IRI prediction model was calibrated and validated using LTPP and other field data. The following is the final calibrated model used in design (in the original model there was an additional term for the amount of patching which was subsequently dropped):

$$IRI = IRI_I + 0.013*CRK + 0.007*SPALL + 0.0015*TFAULT + 0.4*SF \quad (21)$$

N = 157
R^2 = 60 percent
SEE = 0.34 m/km [21.4 in/mile]

where:

IRI_I	=	initial smoothness measured as IRI, m/km.
CRK	=	percentage of slabs with top-down and bottom up transverse cracking and corner cracking (all severities).
SPALL	=	percentage of spalled joints (medium and high severities).
TFAULT	=	total joint faulting cumulated per km, mm.
SF	=	site factor = $(AGE*(1+FI)*(1+P_{0.075}))*10^{-6}$.
AGE	=	pavement age, yr.
FI	=	freezing index, ^{o}C days.
$P_{0.075}$	=	percent subgrade material passing 0.075-mm (#200) sieve.

A plot of the measured and predicted IRI is shown in figure 42 for JPCP. A plot of residual errors (predicted – measured) versus predicted IRI is shown in figure 43.

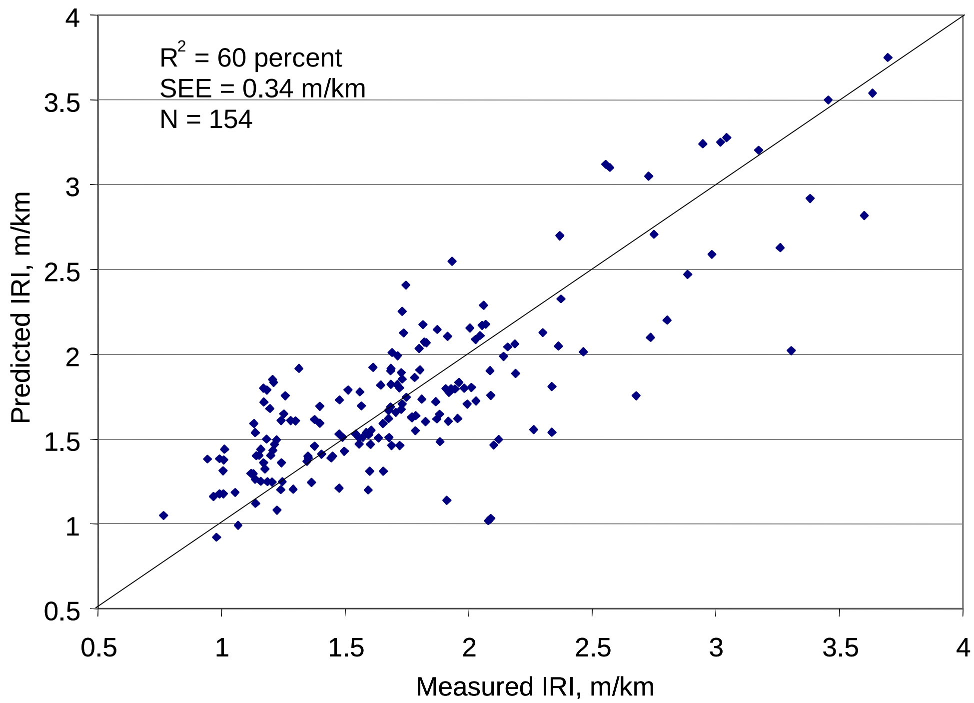

Figure 42. Plot of the predicted versus the actual smoothness for JPCP.

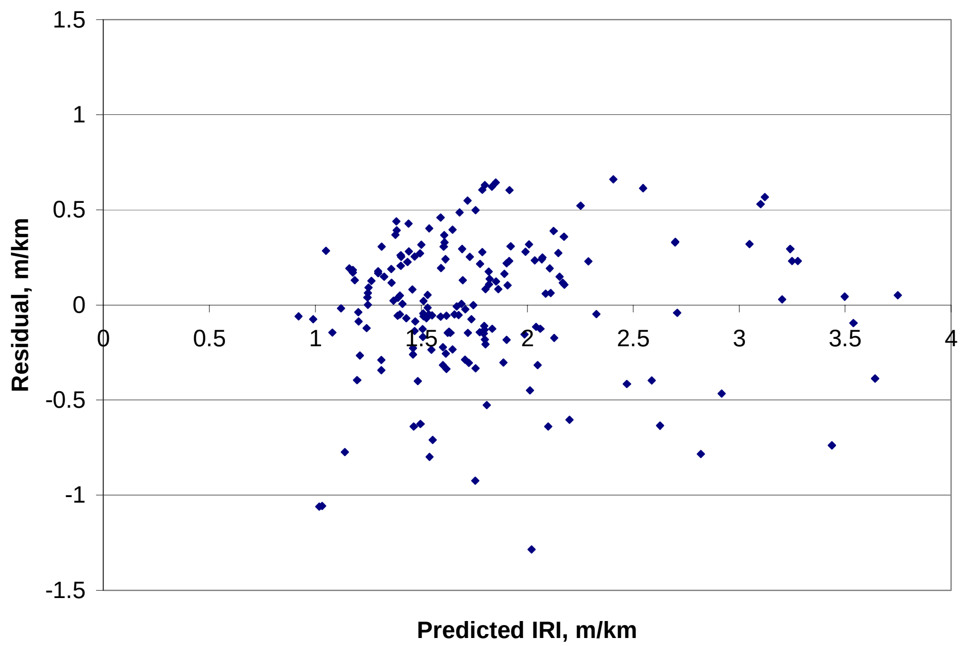

Figure 43. Plot of residual versus predicted smoothness for JPCP.

In developing this calibrated model, actual measured data for cracking, spalling, patching, and total joint faulting, were used. Therefore, the reported SEE reflects the measurement errors associated with these inputs along with model error (lack-of-fit), replication error, and other errors. However, in using this model in design, total joint faulting and cracking are predicted using M-E models and spalling is predicted using an embedded empirical model (see equation 22 below) that has been validated in several previous studies. These distress models have their associated errors which are quite different from the measurement errors representd by the model SEE. It is important to note this distinction between model calibration and the application of the calibrated model for design purposes as it becomes important in the variance analysis discussion provided later.

The empirical model developed for spalling is shown below:

$$SPALL = \left[\frac{AGE}{AGE + 0.01}\right]\left[\frac{100}{1 + 1.005^{(-12*AGE + SCF)}}\right] \tag{22}$$

where
PSPALL = percentage joints spalled (medium- and high-severities).
AGE = pavement age since construction, years.
SCF = scaling factor based on site-, design-, and climate-related variables.

The site factor SCF is defined as the following:

$$SCF = -1400 + 350 * AIR\% * (0.5 + PREFORM) + 3.4 * f'c^{0.4} - 0.2 * (FTCYC * AGE) + 43 * h_{PCC} - 536 * WC\_Ratio \tag{23a}$$

N = 179
R^2 = 78 percent
SEE = 6.8 percent of joints

where

AIR%	= PCC air content, percent.
AGE	= time since construction, years.
PREFORM	= 1 if preformed sealant is present, 0 if other sealant types or no sealant.
f'c	= PCC slab compressive strength, psi.
FTCYC	= average annual number of air freeze-thaw cycles.
hPCC	= PCC slab thickness, in.
WC_Ratio	= PCC water/cement ratio.

<u>CRCP IRI Prediction</u>

The CRCP IRI prediction model was calibrated and validated with field data to assure that it would produce valid results under a variety of climatic and field conditions. The final calibrated CRCP IRI model is shown below (in the original model there were additional terms for the number of patches and extent of transverse cracking):

$$IRI = IRI_I + 0.08*PUNCH + 0.45SF \tag{24}$$

N = 89
R^2 = 63 percent
SEE = 0.21 m/km [14.5 in/mile]

where,

IRI_I	=	initial IRI, m/km.
PUNCH	=	number of medium- and high-severity punchouts/km.
SF	=	site factor = AGE*(1+FI)*(1+$P_{0.075}$)/1000000.
AGE	=	pavement age, yr.
FI	=	freezing index, °C days.
$P_{0.075}$	=	percent subgrade material passing 0.075-mm sieve.

As with JPCP, actual field measured punchouts were used in developing the IRI model. The model SEE reflects the measurement error in estimating this input. However, in design, punchouts are directly predicted using a calibrated M-E model which has its own associated prediction errors.

A plot of the measured and predicted IRI is shown in figure 19 for CRCP. A plot of residual errors (predicted – measured) versus predicted IRI for CRCP is shown in figure 44.

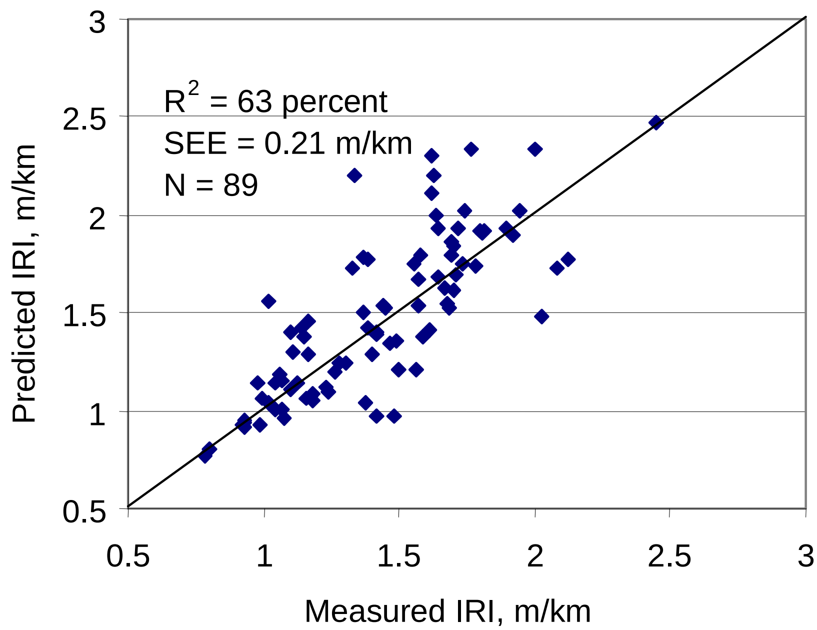

Figure 44. Plot of the predicted versus the actual smoothness for CRCP.

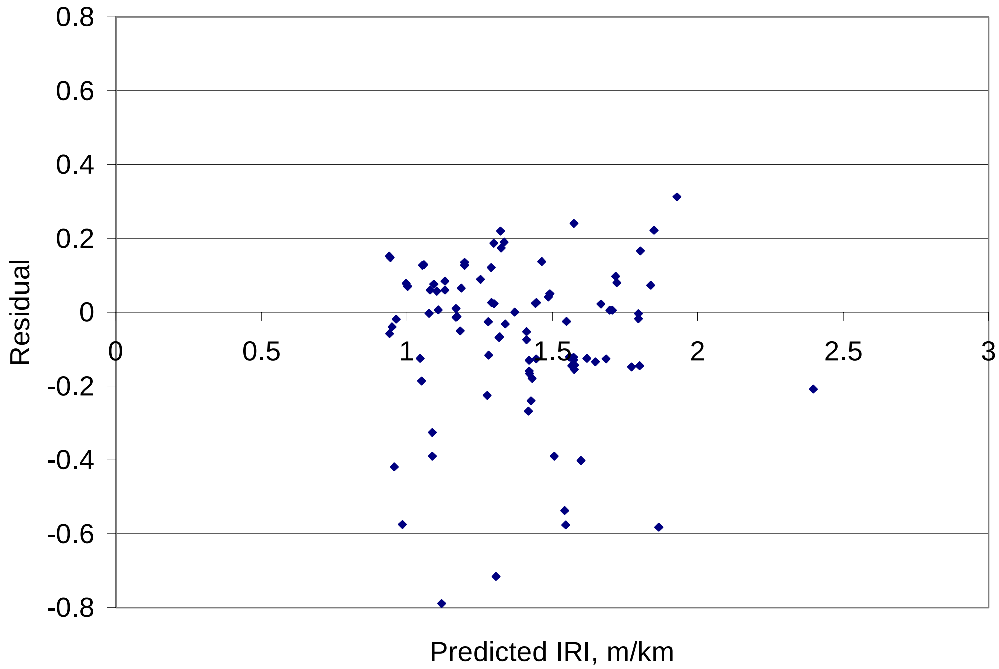

Figure 45. Plot of residual versus predicted smoothness for CRCP.

Defining Variance of the Predicted IRI

An analysis of the measured versus predicted IRI and the residuals was performed for JPCP and CRCP in order to define the stochasticity of the predicted IRI values. This lead to a conclusion that the error in the prediction of the mean project IRI is approximately normally distributed. Thus, the likely variation of IRI around the mean prediction can be defined by the mean of the prediction model (at any time over the design life) and the IRI model SEE. However, a variance analysis of the individual components that make up the model SEE needs to be performed before it can be used in reliability estimation.

<u>Quantification of IRI Model Error through Calibration</u>

The major components of the IRI model SEE are described below:

- **Input Error**: This is the error associated with estimating each design input for each pavement test section used in the calibration process. The input error will depend on the hierarchical levels of input used in the calibration.
- **Error in "actual" or "measured" IRI**: This is the error associated with measuring the IRI value being predicted from each pavement section used in calibration. This error is basically the testing repeatability error.
- **Pure Error**: This error represents the random or normal variation between the IRI's exhibited by supposedly replicate sections. The causes of this error are unknown, but variations caused by construction processes and materials variations partially explain its occurrence.

- **Model or Lack-of-Fit Error**: This error reflects the inability of the model to predict actual pavement performance (e.g., IRI) due to deficiencies in the model such of lack of specific inputs or inadequate functional form or damage accumulation algorithms. This is the real model error associated with prediction. Once the models have undergone final calibration and validation, this error remains a constant until the model is changed in future.

These components of variance can be mathematically expressed as follows:

IRI Prediction Error = (Actual IRI) – (Predicted IRI)

Variance {Prediction Error} = Variance {Actual IRI} + Variance {Predicted IRI} + Co-variance {Actual IRI, predicted IRI}

or,

$$V_e = V_t + V_p - 2\ r\ \mathrm{Sqrt}(V_t) * \mathrm{Sqrt}(V_p) \quad (25)$$

where,

V_e	=	total error variance associated with predicting IRI.
V_t	=	variance of measuring the IRI (basically testing repeatability).
V_p	=	variance of IRI prediction model = $V_i + V_r + V_m$
V_i	=	variance caused by estimating model inputs
V_r	=	variance due to replication.
V_m	=	variance due to the actual model deficiencies.
r	=	correlation coefficient between actual and predicted IRI (can be estimated from model R^2).

In the variance component analysis, the goal will be to identify the error contributed by all other factors except that from the input variability. For the IRI model, since the primary inputs are the pavement distresses, this would amount to factoring the contribution of the measurement error of these distresses out of the overall SEE. When this error is removed from the model SEE, the remaining error causing uncertainity in the IRI prediction is due to factors such as model lack of fit (V_m) and pure or replication error (V_r).

The first step in the variance component analysis therefore is identify the known terms in equation 25. These are listed below:

- The total variance of the IRI prediction model, V_e, is the square of model SEE estimated at the end of the calibration and validation process.
- The typical variance in measuring IRI, V_t, can be approximated based on existing literature.
- The variance associated with the measurement of each of the individual distresses, V_i, can also be estimated from literature and experience.

The unknown parameters from equation 25 are therefore, the replication error, V_r, and the model lack-of-fit error, V_m. These quantities can be lumped together and the variance due to overall model deficiencies can be estimated from equation (25).

Derivation of Variance Model for IRI of JPCP

The model to predict JPCP IRI is provided in equation (21). The variance of the initial IRI_0, CRK, TFAULT, and SPALL are directly considered in design. The variables in the SF term either have zero variance (i.e. AGE) or are already considered in the overall model variance. Therefore, the overall variance of the JPCP IRI model is as follows:

$$Var[IRI] = Var[IRI_i + 0.000169 \times Var[CRK] + 0.000049 \times Var[SPALL] + \\ + 0.00000225 \times Var[TFAULT] + S_e^2 \tag{26}$$

where:

IRI	=	predicted IRI (m/km)
IRIi	=	initial IRI (m/km)
CRK	=	percentage of slabs with transverse cracking and corner breaks (all severities)
SPALL	=	percentage of joints with spalling (medium and high severities)
TFAULT	=	total joint faulting cumulated per km, mm
Var[……]	=	variance of each parameter
SF	=	site factor
S_e	=	magnitude of the overall JPCP IRI model error

Equation (26) could be directly used for design if the proper variances for cracking prediction, faulting prediction, spalling prediction, and initial IRI were known. These values are obtained directly from the calibration results for each model.

Assessing S_e, Overall Model Error for JPCP IRI

The model error (Se) is also required as shown in equation 26. A value of 0.34 m/km is reported for the JPCP IRI model SEE. This value represents a total variation in prediction of IRI using the LTPP data base for JPCP pavements. It is based on 157 data points from JPCP spread over North America. This value could be used, however, it is higher than the value needed for design because it includes "measurement" error for each distress and IRI. The following equations provide for a slightly reduced estimate of Se.

The IRI model is rearranged as follows to solve for IRI prediciton error.

IRI Prediction error = IRImeas - IRIpred

Var[IRIpe] = Var[IRIm] + V[IRIp] + Co-Variance of IRIm and IRIp

Var[IRIpe] = Var[IRIm] + V[IRIp] – 2r*Sqrt(V[IRIm]) * Sqrt(V[IRIp])

Var[IRIm] represents the variation of initial IRI construction. A CV of 2 percent is assumed for this error. Note that this represents the actual measurement repeatability error in measuring IRI.

$$Var[IRIm] = [2.0 * 0.02]^2 = 0.0016$$
$$V[IRIp] = V[Inputs] + V[model + pure\ error]$$

The V[Inputs] represents the variations due to measurement errors in the field of each of these specific distresses and smoothness (e.g., IRI, transverse cracking, joint spalling, and joint faulting).

$$V[Inputs] = V[IRIi] + 0.000169*V[CRK] + 0.000049*V[SPALL] + 0.00000225*V[TFAULT]$$

These variances are estimated by assuming a coefficient of variation of measurement for each distress and IRI (e.g. 25 percent coefficient of variation assumed for measurement of joint spalling). Typical COV values for cracking and spalling measurements were taken from LTPP Tech Brief "Variability of Pavement Distress Data from Manual Surveys (FHWA Pub. No. FHWA-RD-00-160)."

$$V[Inputs] = [1.3*0.1]^2 + 0.000169*[15 * 0.15]^2 + 0.000049*[20*0.25]^2 + 0.00000225*[200*2.54* 0.15]^2 = 0.03204 \quad \text{(note all units are in SI)}$$

The correlation coefficient, r, between predicted IRI and measured IRI is sqrt(0.5878) (or sqrt $[R^2]$)= 0.766.

The V[model error] is what we are trying to determine and it can now be calculated as follows:

$$Var[IRIpe] = Var[IRIm] + V[Inputs] + V[model + pure\ error] - 2 * 0.766 * Sqrt(V[IRIm]) * Sqrt(\{V[Inputs] + V[model + pure\ error]\})$$

The overall total error associated with the IRI model is 0.34 m/km. The square of this is the variance in Var[IRIpe].

$$(0.34)^2 = 0.0016 + 0.03204 + V[model\ error] - 2 * 0.766 * Sqrt(0.0016) * Sqrt(0.03204 + Var[model + pure\ error])$$

The solution for Var[model + pure error] is 0.104613, and the standard error is 0.3234. This value will be used in the JPCP IRI model for design reliability purposes.

Derivation of Variance Model for IRI of CRCP Model

The SF represents Age, P200, and FI. The variance of age is 0 and the variance of P200 and FI are considered in overall error term derived in calibration. Thus, the variance associated with SF is zero.

The variance model for CRCP punchouts is as follows.

$$Var[IRI] = Var[IRI_0] + 0.0064 \times Var[PUNCH] + S_e^2$$

where:

IRI	=	predicted IRI (m/km)
IRI_0	=	initial IRI (m/km)
PUNCH	=	number of punchouts/km
Var[……]	=	variance of each parameter
ε_{IRI}	=	model error ($\mu = 0.$, σ_e)
S_e	=	magnitude of the overall CRCP IRI model error

The variance equation could be directly used for design if the proper variances for punchout prediction and initial IRI were known. These values are obtained directly from the calibration results for each model.

<u>Assessing Se, Model Error for CRCP IRI</u>

The model error (Se) is also required as shown in the equation variance. A value of 0.21 m/km is reported for the CRCP IRI model SEE. This value represents a total variation in prediction of IRI using the LTPP data base for CRCP pavements. It is based on 89 data points from CRCP spread over North America. This value could be used, however, it is higher than the value needed for design because it includes “measurement” error for punchouts and IRI. The following equations provide for a slightly reduced estimate of Se.

The IRI model is rearranged as follows to solve for IRI prediciton error.

IRI Prediction error = IRImeas - IRIpred

Var[IRIpe] = Var[IRIm] + V[IRIp] + Co-Variance of IRIm and IRIp

Var[IRIpe] = Var[IRIm] + V[IRIp] – 2r*Sqrt(V[IRIm]) * Sqrt(V[IRIp])

Var[IRIm] represents the variation of initial IRI construction. A CV of 2 percent is assumed for this error.

Var[IRIm] = $[2.0 * 0.02]^2$ = 0.0016

V[IRIp] = V[Inputs] + V[model + pure error]

The V[Inputs] represents the variations due to measurement errors in the field of each of these specific distresses and smoothness (e.g., IRI, transverse cracking, jiont spalling, and joint faulting).

$$V[Inputs] = V[IRIi] + 0.0064*V[PUNCH]$$

These variances are estimated by assuming a coefficient of variation of measurement for initial IRI and punchouts and a mean balue for each of these inputs. A COV value of 50% is assumed for punchout measurement as it appears to be fairly difficult to consistently identify punchouts in the field.

$$V[Inputs] = [1.3*0.1]^2 + 0.0064*[5 * 0.10]^2 = 0.0185 \text{ (note all units are in SI)}$$

The correlation coefficient, r, between predicted IRI and measured IRI is sqrt(0.5878) (or sqrt [R^2])= 0.7937.

The V[model + pure] is what we are trying to determine and it can now be calculated as follows:

$$\begin{aligned} Var[IRIpe] &= Var[IRIm] + V[Inputs] + V[model + pure error] - \\ &\quad 2 * 0.7937 * Sqrt(V[IRIm]) * Sqrt(\{V[Inputs] + V[model + pure error]\}) \end{aligned}$$

The overall total error associated with the IRI model is 0.34 m/km. The square of this is the variance in Var[IRIpe].

$$\begin{aligned} 0.34^\wedge 2 &= 0.0016 + 0.0185 + V[model error] - \\ &\quad 2 * 0.7937 * Sqrt(0.0016) * Sqrt(0.0185 + Var[model + pure error]) \end{aligned}$$

The solution for Var[model + pure error] is 0.0253, and the standard error is 0.1592. This value will be used in the CRCP IRI model.

Models for IRI Variance in Flexible and Semi-Rigid Pavements

The methodology was applied directly on the generated variables used to estimate the IRI as a measure of road smoothness for the section. These variables include load-associated and thermal distresses, initial smoothness, age, patching and site conditions.

The final models to predict IRI for HMA surfaced pavements is base type dependent and listed below: Following each model developed in this project, the models for expected IRI value and corresponding variance is presented, as derived from First-Order, Second-Moment (FOSM) method.

<u>Unbound Aggregate Bases and Subbases:</u>

$$IRI = IRI_o + 0.0463(SF)[e^{Age/20} - 1] + 0.00384(FC) + 0.1834(COV_{RD}) + 0.00119(TC) + 0.00736(BC) + 0.00155(SLCNWP_{MH}) + \varepsilon_{IRI} \tag{27}$$

$$E[IRI] = \overline{IRI}_0 + 0.0463(\overline{SF})[e^{0.05Age} - 1] + 0.00384(\overline{FC}) + 0.1834(\overline{COV}_{RD}) + 0.00119(\overline{TC}) + 0.00736(\overline{BC}) + 0.00155(\overline{SLCNWP}_{MH}) \tag{28}$$

$$Var[IRI] = Var[IRI_0] + \{(0.0463(e^{0.05Age}) - 0.0463)\}^2 Var[SF] + 1.47456 \times 10^{-5} Var[FC] + 3.36356 \times 10^{-2} Var[COV_{RD}] + 1.4161 \times 10^{-6} Var[TC] + 5.41696 \times 10^{-5} Var[BC] + 2.4025 \times 10^{-6} Var[SLCNWP_{MH}] + S_e^2 \tag{29}$$

where:

E[IRI]	=	predicted (expected) IRI (m/km)
Var[IRI]	=	IRI variance
IRI_0	=	initial IRI (m/km)
SF	=	site factor
Age	=	age of pavement (years)
FC	=	fatigue cracking, percent of wheel path area (%)
COV_{RD}	=	coefficient of variation of rut depth (%)
TC	=	length of transverse cracks (m/km)
BC	=	area of block cracking, percent of total area (%)
$SLCNWP_{MH}$	=	moderate and high severity length sealed longitudinal cracks outside wheel path (m/km)
S_e	=	0.387m/km; standard error of estimate for the model
ε_{IRI}	=	model error ($\mu = 0.$, σ_e)

<u>Asphalt Treated Bases:</u>

$$IRI = IRI_o + 0.0099947(\mathrm{Age}) + 0.0005183(\mathrm{FI}) + 0.00235(FC) + 18.36/(TCS_H) + 0.9694(P_H) + \varepsilon_{IRI} \tag{30}$$

$$E[IRI] = \overline{IRI}_0 + 0.0099947(Age) + 0.0005183(\overline{FI}) + 0.00235(\overline{FC}) + 18.36\left[\frac{1}{\overline{TCS}_H}\right] + 0.9694(\overline{P}_H) + \frac{1}{2}\left[\frac{36.72}{\overline{TCS}_H^3}\right] \times Var[TCS_H] \tag{31}$$

$$Var[IRI] = Var[IRI_0] + 2.6863 \times 10^{-7} Var[FI] + 5.5225 \times 10^{-6} Var[FC] + \frac{337.09}{\overline{TCS}_H^4} Var[TCS_H] + 0.9397 \times Var[P_H] + S_e^2 \tag{32}$$

where:

E[IRI]	=	predicted (expected) IRI (m/km)
Var[IRI]	=	IRI variance
IRI_0	=	initial IRI (m/km)
Age	=	age after construction (years)
FI	=	annual freezing index (°C days)
FC	=	fatigue cracking, percent of wheel path area (%)
TCS_H	=	high severity transverse crack spacing (m)
P_H	=	high severity area of patching, percent of total area (%)
S_e	=	0.292 m/km; standard error of estimate for the model
ε_{IRI}	=	model error ($\mu = 0.$, σ_e)

<u>Cement or Pozzolonic Treated Bases:</u>

$$IRI = IRI_O + 0.00732(FC) + 0.07647(SD_{RD}) + 0.0001449(TC) + 0.00842(BC) + 0.0002115(LCNWP_{MH}) + \varepsilon_{IRI} \quad (33)$$

$$E[IRI] = \overline{IRI}_0 + 0.00732(\overline{FC}) + 0.07647(\overline{SD}_{RD}) + 0.0001449(\overline{TC}) + 0.00842(\overline{BC}) + 0.0002115(\overline{LCNWP}_{MH}) \quad (34)$$

$$Var[IRI] = Var[IRI_0] + 5.358\times10^{-5}Var[FC] + 5.848\times10^{-3}Var[SD_{RD}] + 2.0996\times10^{-8}Var[TC] + 7.0896\times10^{-5}Var[BC] + 4.473\times10^{-8}Var[LCNWP_{MH}] + S_e^2 \quad (35)$$

where:

E[IRI]	=	predicted (expected) IRI (m/km)
Var[IRI]	=	IRI variance
IRI_0	=	initial IRI (m/km)
FC	=	fatigue cracking, percent of wheel path area (%)
SD_{RD}	=	standard deviation of rut depth (mm)
TC	=	length of transverse cracks (m/km)
BC	=	area of block cracking, percent of total area (%)
$LCNWP_{MH}$	=	moderate and high severity length of longitudinal cracks outside wheel path (m/km)
S_e	=	standard error of estimate for the model
ε_{IRI}	=	model error ($\mu = 0.$, σ_e)

HMA Overlays Placed on Flexible Pavements:

$$IRI = IRI_O + 0.011505(Age) + 0.0035986(FC) + 3.4300573(1/TCS_{MH}) + 0.0112407(P_{MH}) + 9.04244(\mathrm{PH}) + 0.000723(SLCNWP) + \varepsilon_{\mathrm{IRI}} \quad (36)$$

$$E[IRI] = \overline{IRI}_0 + 0.011505(Age) + 0.0035986(\overline{FC}) + 3.4300573(\frac{1}{\overline{TCS}_{MH}}) + 0.0112407(\overline{P}_{MH}) + 9.04244(\overline{PH}) + 0.000723(\overline{SLCNWP}) + \frac{1}{2}\left[\frac{6.8601}{\overline{TCS}^3_{MH}}\right] \times Var[TCS_{MH}] \quad (37)$$

$$Var[\,IRI\,] = Var[\,IRI_0\,] + 1.295 \times 10^{-5} Var[\,FC\,] + \frac{11.765}{\overline{TC}^4_{MH}} Var[\,TCS_{MH}\,] + 1.2635 \times 10^{-4} Var[\,P_{MH}\,] + 81.766 \times Var[\,PH\,] + 5.2273 \times 10^{-7} Var[\,SLCNWP\,) + S_e^2 \quad (38)$$

where:

E[IRI]	=	predicted (expected) IRI (m/km)
Var[IRI]	=	IRI variance
IRI_0	=	initial IRI (m/km)
Age	=	age of pavement (years)
FC	=	fatigue cracking, percent of wheel path area (%)
TCS_{MH}	=	moderate and high severity transverse crack spacing (m)
P_{MH}	=	moderate and high severity area of patching, percent of total area (%)
PH	=	pot holes, percent of total lane area (%)
SLCNWP	=	length sealed longitudinal cracks outside wheel path (m/km)
S_e	=	0.179 m/km (standard error of estimate for the model)
ε_{IRI}	=	model error ($\mu = 0.$, σ_e)

HMA Overlays Placed on Rigid Pavements:

$$IRI = IRI_O + 0.0082627(\mathrm{Age}) + 0.0221832(RD) + 1.33041\ (1/(TCS_{MH}) \quad + \varepsilon_{\mathrm{IRI}} \quad (39)$$

$$E[IRI] = \overline{IRI}_0 + 0.0082627(Age) + 0.0221832(\overline{RD}) + 1.33041\left[\frac{1}{\overline{TCS}_{MH}}\right] + \frac{1}{2}\left[\frac{2.6608}{\overline{TCS}^3_{MH}}\right] \times Var[TCS_{MH}] \quad (40)$$

$$Var[IRI] = Var[IRI_0] + 4.9209 \times 10^{-4} Var[RD] + \left[\frac{1.770}{\overline{TCS}_{MH}^{4}} \right] Var[TCS_{MH}] + S_e^2 \qquad (41)$$

where:

E[IRI]	=	predicted (expected) IRI (m/km)
Var[IRI]	=	IRI variance
IRI_0	=	initial IRI (m/km)
Age	=	age of pavement (years)
RD	=	rut depth (mm)
TCS_{MH}	=	moderate and high severity transverse crack spacing (m)
S_e	=	0.197 m/km (standard error of estimate for the model)
ε_{IRI}	=	model error ($\mu = 0.$, σ_e)

Site Factor for Flexible Pavement Models

$$SF = \left[\frac{(R_{SD})(P_{0.075}+1)(PI)}{2 \times 10^4} \right] + \left[\frac{\ln(FI+1)(P_{0.02}+1)\ln(R_m+1)}{10} \right] \qquad (42)$$

$$E[SF] = \left[\frac{(R_{SD})(\overline{P}_{0.075}+1)(\overline{PI})}{2 \times 10^4} \right] + \left[\frac{\ln(\overline{FI}+1)(\overline{P}_{0.02}+1)\ln(\overline{R}_m+1)}{10} \right] \qquad (43)$$

$$\begin{aligned} Var[SF] = {} & \left(\frac{R_{SD} \times \overline{PI}}{2 \times 10^4} \right)^2 Var[P_{0.075}] + \left(\frac{R_{SD} \times (\overline{P}_{0.075}+1)}{2 \times 10^4} \right)^2 Var[PI] + \\ & \left(\frac{(\overline{P}_{0.02}+1) \times \ln(\overline{R}_m+1)}{10(\overline{FI}+1)} \right)^2 Var[FI] + \left(\frac{\ln(\overline{FI}+1) \times \ln(\overline{R}_m+1)}{10} \right)^2 Var[P_{0.02}] + \\ & \left(\frac{\ln(\overline{FI}+1) \times (\overline{P}_{0.02}+1)}{10(\overline{R}_m+1)} \right)^2 Var[R_m] \end{aligned} \qquad (44)$$

where:

SF	=	site factor
R_{SD}	=	standard deviation of the monthly rainfall (mm)
R_m	=	average annual rainfall (mm)
$P_{0.075}$	=	percent passing the 0.075 mm sieve (%)
$P_{0.02}$	=	percent passing the 0.02 mm sieve (%)
PI	=	plasticity index (%)
FI	=	annual freezing index (^{o}C days)

Other Distresses in Flexible Pavements

Load-associated (fatigue cracking and rutting) and thermal (thermal cracking) distresses are estimated using rational analysis. However, IRI models also include independent distress variables that are not predicted through available transfer functions. These distresses include block cracking, patching, longitudinal cracking outside the wheelpath area, crack sealing and potholes.

For the 2002 Design Guide, models were developed based on the LTPP database (DataPave 3.0) to provide estimates of those distresses as a function of time. In addition, trends for the model errors allowed estimates for variability of these distresses based on a user-defined *Distress Potential* variable that is estimated based on past experience for local conditions and is user input.

- *Total Area of Block Cracking (Unbound Granular Base)*

$$(BC)_T = \frac{100}{1+\exp^{(DP-1.008\,age)}} \tag{45}$$

Where $(BC)_T$ in the above equation is in % of total pavement area, age in years, "DP" defines the potential level for block cracking and is defined in the following table:

Table 20. Distress Potential for Block Cracking (Unbound Granular Base)

Level "*DP*"	**DP**
High	10
Med	20
Low	30
None	40

Figure 46 shows the predicted versus actual (LTPP database) area of block cracking for pavements with granular base.

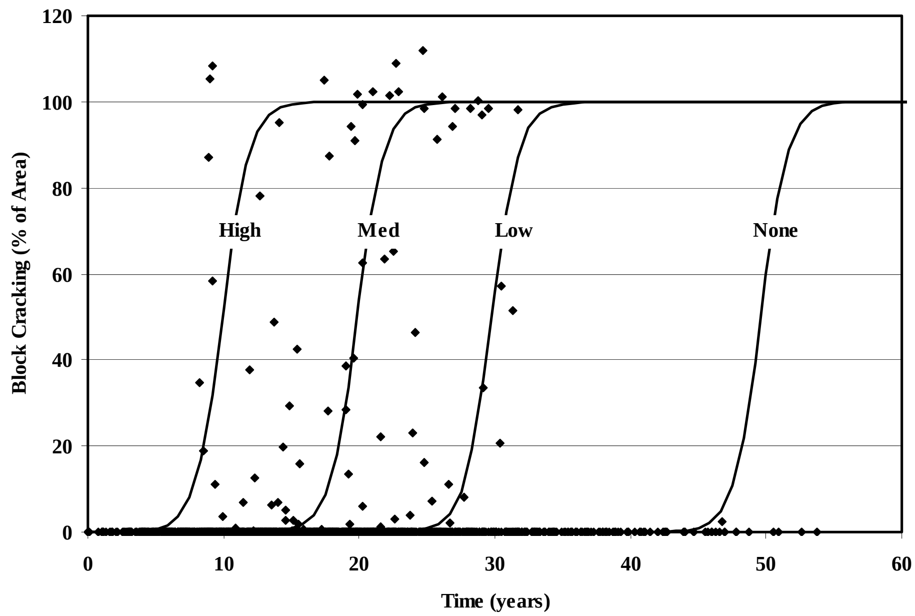

Figure 46. Block Cracking Prediction Curves for Pavements with Granular Base

The standard error for the model is estimated through the following relationship:

$$S_{BC}^2 = 15 - 0.375DP \tag{46}$$

- *Total Area of Block Cracking (Cement Treated Base)*

$$(BC)_T = \frac{100}{1 + \exp^{(DP - 1.008\, age)}} \tag{47}$$

Where $(BC)_T$ in the above equation is in % of total pavement area, age in years, "DP" defines the potential level for block cracking and is defined in the following table:

Table 21. Distress Potential for Block Cracking (Cement Treated Base)

Level "*DP*"	**DP**
High	6.5
Med	14.25
Low	22
None	32

Figure 47 shows the predicted versus actual (LTPP database) area of block cracking for pavements with cement treated bases.

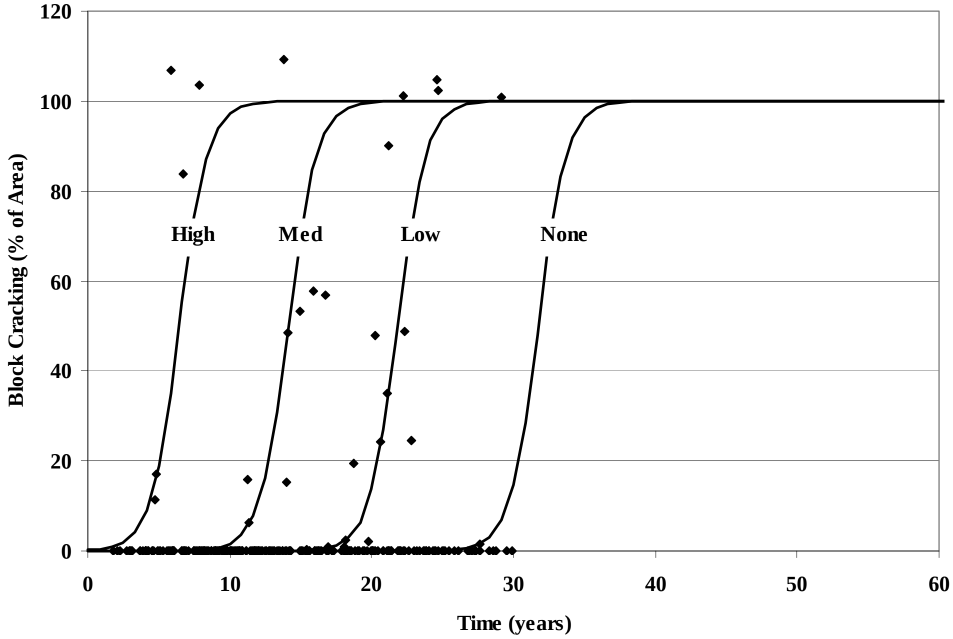

Figure 47. Block Cracking Prediction Curves for Pavements with Cement Treated Base

The standard error for the model is estimated through the following relationship:

$$S_{BC}^2 = 13.09 - 0.4091DP \qquad (48)$$

- *Sealed Longitudinal Cracks Outside Wheelpath*

$$(LC_{SNWP})_{MH} = 2000\exp[-\exp(DP - 0.15age)] \qquad (49)$$

Where $(LC_{SNWP})_{MH}$ in the above equation is the length of medium and high severity sealed longitudinal cracks outside wheelpath area in m/km, age in years, "DP" defines the potential level for crack sealing and is defined in the following table:

Table 22. Distress Potential for Sealed Longitudinal Cracks Outside Wheelpath

Level "*DP*"	**DP**
High	1.9
Med	3.4
Low	5
None	8.5

Figure 48 shows the predicted versus actual (LTPP database) length of longitudinal cracks.

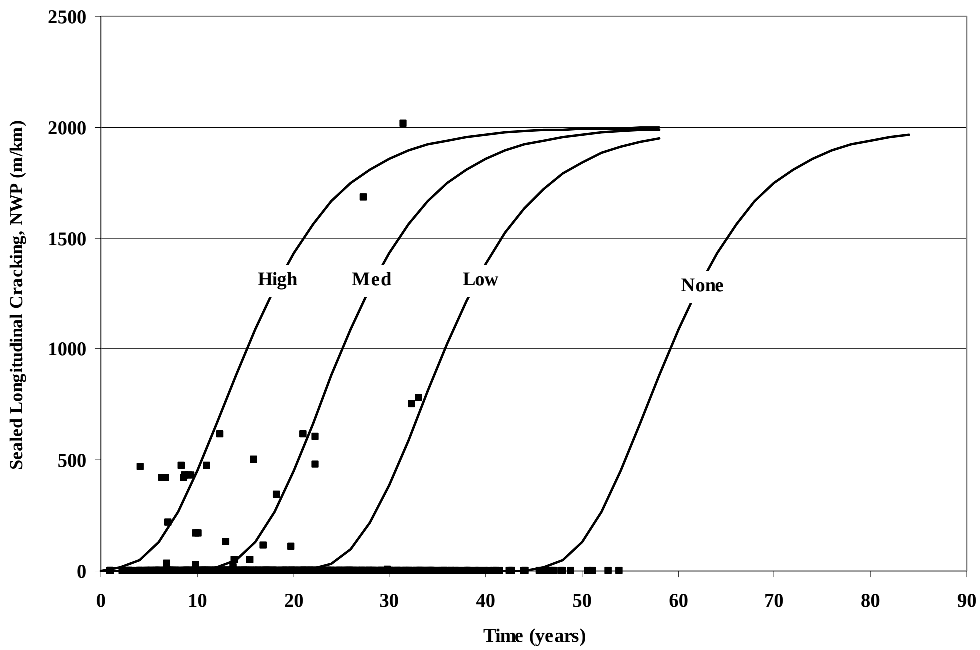

Figure 48: Sealed Longitudinal Cracking (NWP) as a Function of Time

The model variance is estimated through the following relationship:

$$S^2_{LC_{SNWP}} = 140 - 16.47DP \qquad (50)$$

- *Longitudinal Cracks Outside Wheelpath (Cement Treated Base)*

$$(LC_{NWP})_{MH} = 2000\ \exp[-\exp(DP - 0.34\ age)] \qquad (51)$$

Where $(LC_{NWP})_{MH}$ in the above equation is the length of medium and high severity longitudinal cracks outside wheelpath area in m/km, age in years, "DP" defines the potential level for cracking ouside the wheelpath area and is defined in the following table:

Table 23. Distress Potential for Longitudinal Cracks Outside Wheelpath (CTB)

Level "*DP*"	**DP**
High	3.7
Med	6.85
Low	10
None	13.5

Figure 49 shows the predicted versus actual (LTPP database) longitudinal cracks outside wheelpath for pavements with cement treated base.

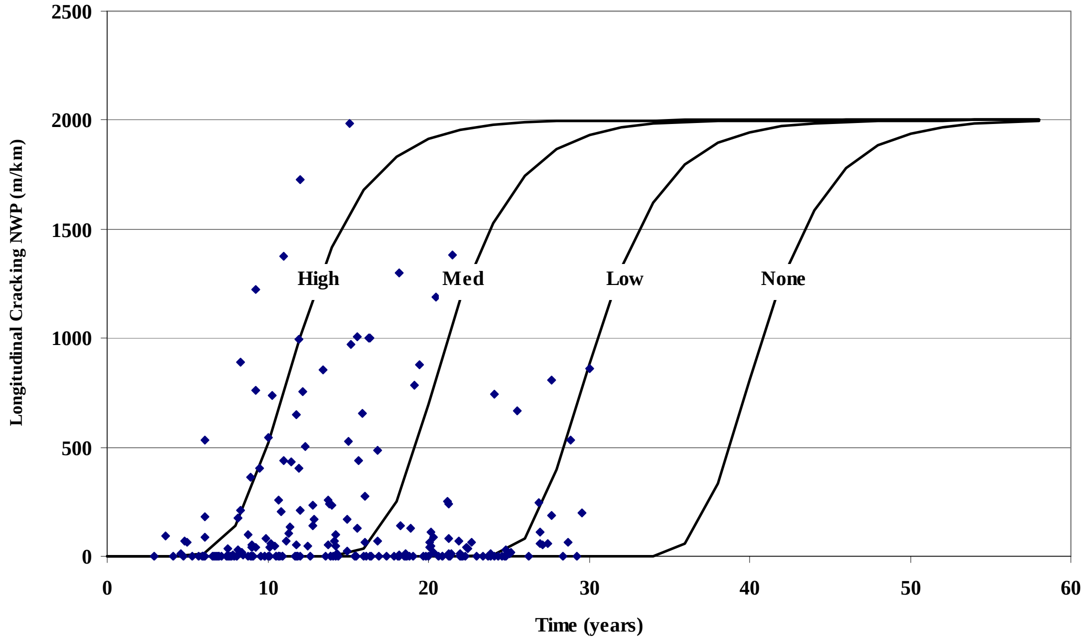

Figure 49. Longitudinal Cracking (NWP) as a Function of Time with CTB for New Flexible Pavement

The standard error for the model is estimated through the following relationship:

$$S^2_{LC_{NWP}} = 514.3 - 38.10DP \tag{52}$$

- *Longitudinal Cracks Outside Wheelpath (HMA Overlay)*

$$(LC_{NWP})_{MH} = 2000\exp[-\exp(DP - 1.32\,age)] \tag{53}$$

Where $(LC_{NWP})_{MH}$ in the above equation is the length of medium and high severity longitudinal cracks outside wheelpath area in m/km, age in years, "DP" defines the potential level for cracking outside the wheelpath area and is defined in the following table:

Table 24. Distress Potential for Long. Cracks Outside Wheelpath (HMA Overlays)

Level *"DP"*	**DP**
High	4.0
Med	8.85
Low	13.7
None	35

Figure 50 shows the predicted versus actual (LTPP database) longitudinal cracks outside wheelpath for HMA overlays.

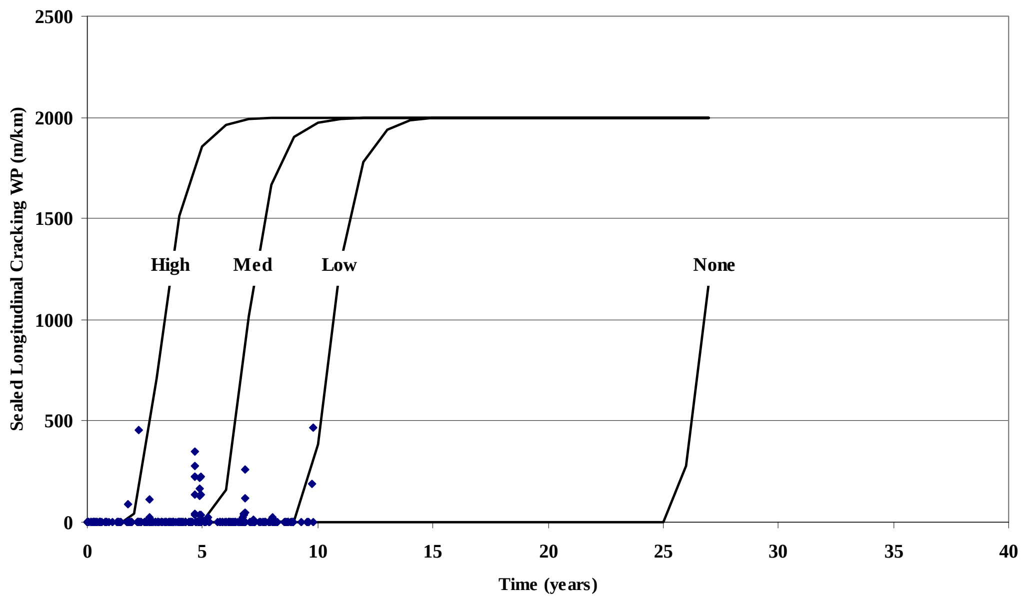

Figure 50. Longitudinal Cracking Function of Time for HMA Overlays

The model variance is estimated through the following relationship:

$$S^2_{LC_{NWP}} = 175 - 5.00DP \tag{54}$$

- *Patch Area (New Pavements)*

$$(P)_H = 20 \exp[-\exp(DP - 0.328\, age)] \tag{55}$$

Where $(P)_H$ in the above equation is in % of total lane area, age in years, "DP" defines the potential level for high severity patching and is defined in the following table:

Table 25. Distress Potential for Patch Area in New Pavements

Level "*DP*"	DP
High	5.45
Med	8.47
Low	11.5
None	15.0

Figure 51 shows the predicted versus actual (LTPP database) patch area in new pavements.

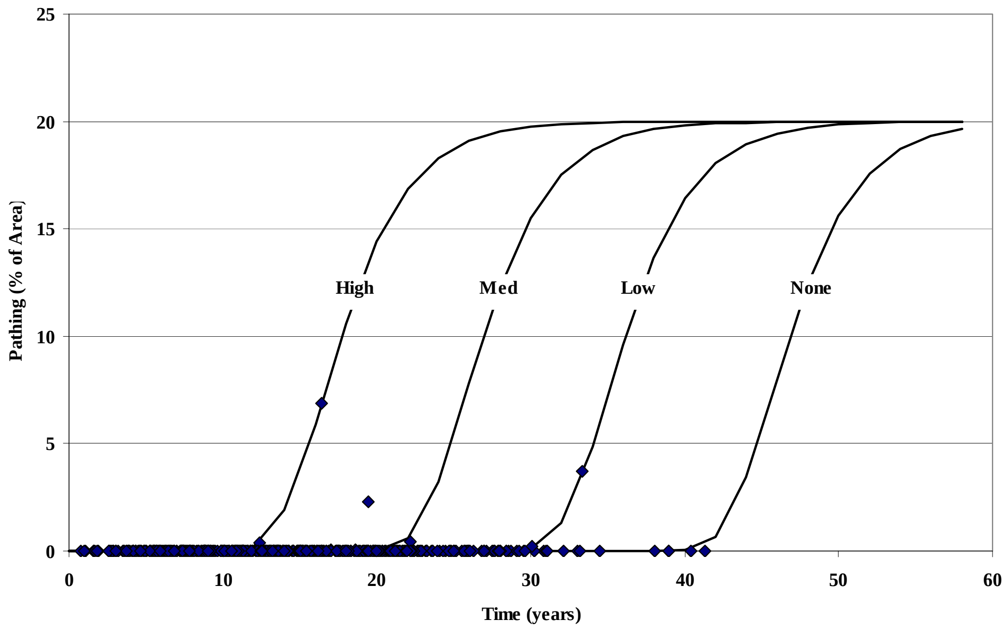

Figure 51. Patching Trends for New Flexible Pavements

The model variance is estimated through the following relationship:

$$S_P^2 = 1.125 - 0.0750DP \tag{56}$$

- *Patch Area (HMA Overlay)*

$$(P)_{MH} = 20\exp[-\exp(DP - 0.328\,age)] \tag{57}$$

Where $(P)_{MH}$ in the above equation is in % of total lane area, age in years, "DP" defines the potential level for medium and high severity patching and is defined in the following table:

Table 26. Distress Potential for Patch Area in HMA Overlaid Pavements

Level "*DP*"	**DP**
High	3.3
Med	3.9
Low	4.5
None	8.0

Figure 52 shows the predicted versus actual (LTPP database) patch area for HMA overlays.

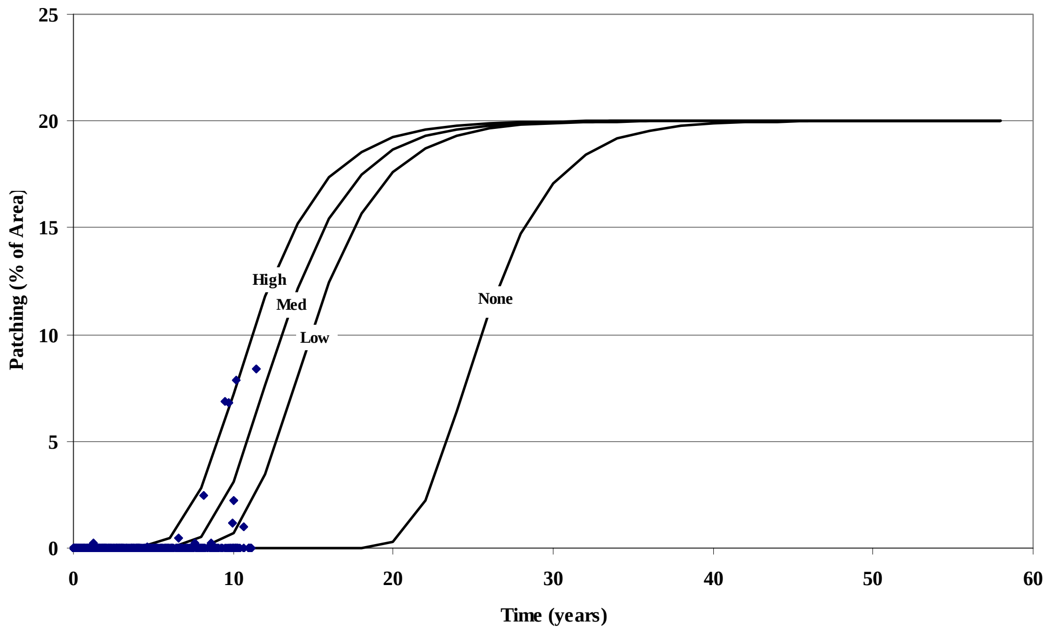

Figure 52. Patching Trends for HMA Overlays

The model variance is estimated through the following relationship:

$$S_P^2 = 0.3333 - 0.04167DP \quad (58)$$

- *Pot Holes (HMA Overlay)*

$$(PH)_T = 0.1\exp[-\exp(DP - 0.914\,age)] \quad (59)$$

Where (PH) in the above equation is in % of total lane area, age in years, "DP" defines the potential level for presence of potholes and is defined in the following table:

Table 27. Distress Potential for Pot Holes in HMA Overlaid Pavements

Level *"DP"*	**DP**
High	4.1
Med	6.3
Low	8.5
None	20.0

Figure 53 shows the predicted versus actual (LTPP database) percent of potholes in HMA overlaid pavements.

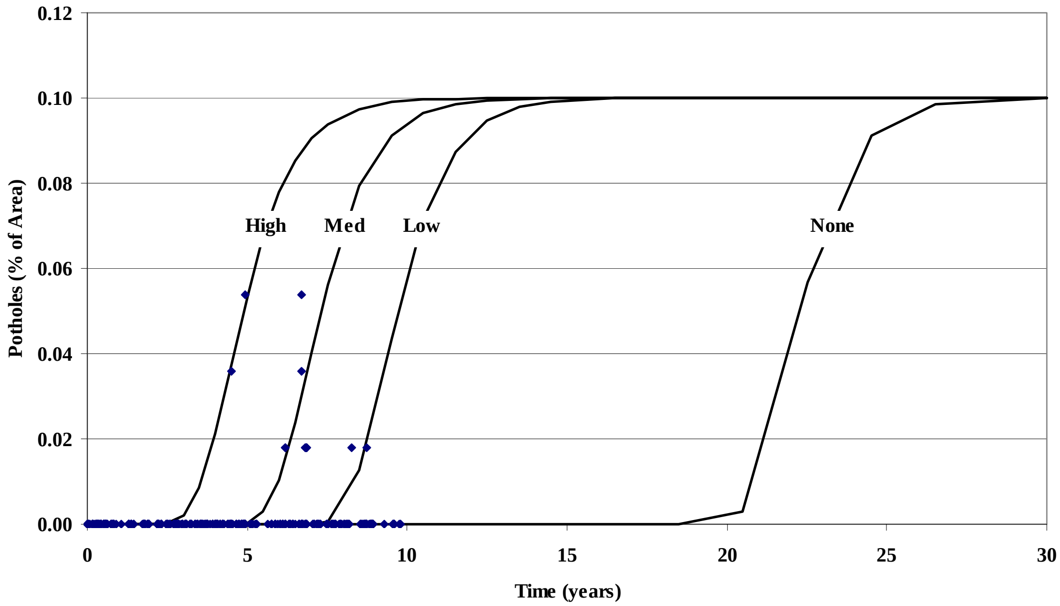

Figure 53. Potholes Trends for HMA Overlays

The model variance is estimated through the following relationship:

$$S_{BC\%}^{2} = 0.01875 - 0.000937DP \tag{60}$$

Assessment of Reliability

Using both expected and variance values for the IRI prediction and assuming a normal distribution, for each month the probability R that IRI is less than a user-defined failure criteria is estimated. The reliability concept is illustrated using figure 54.

For month i, IRI probability distribution (IRIavrg, SIRI) is represented. The S_{IRI} estimate at any given expected IRI value includes contributions of the model error as well as the individual contributions from each distress model (faulting, cracking, and spalling for JPCP and punchouts for CRCP). Assuming a normal distribution and a user-defined failure criteria, probability α that IRI > IRIfailure is found. Reliability is estimated as R = 1 - α.

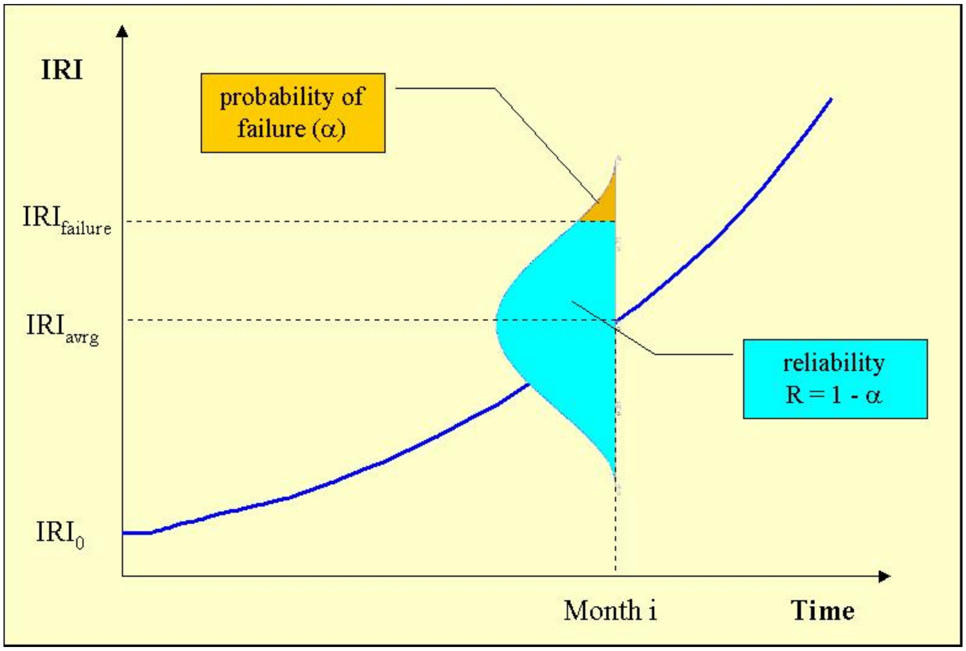

Figure 54.   Design reliability concept for IRI (from M. Ayres).

Figure 55 below shows the reliability estimate curves at 50 and 95 percent for a given JPCP section. Figure 56 shows reliability estimate curves at 50 and 95 percent levels for a given CRCP section. These estimates were generated based on using the 2002 Design Guide software after implementing the reliability approach discussed above.

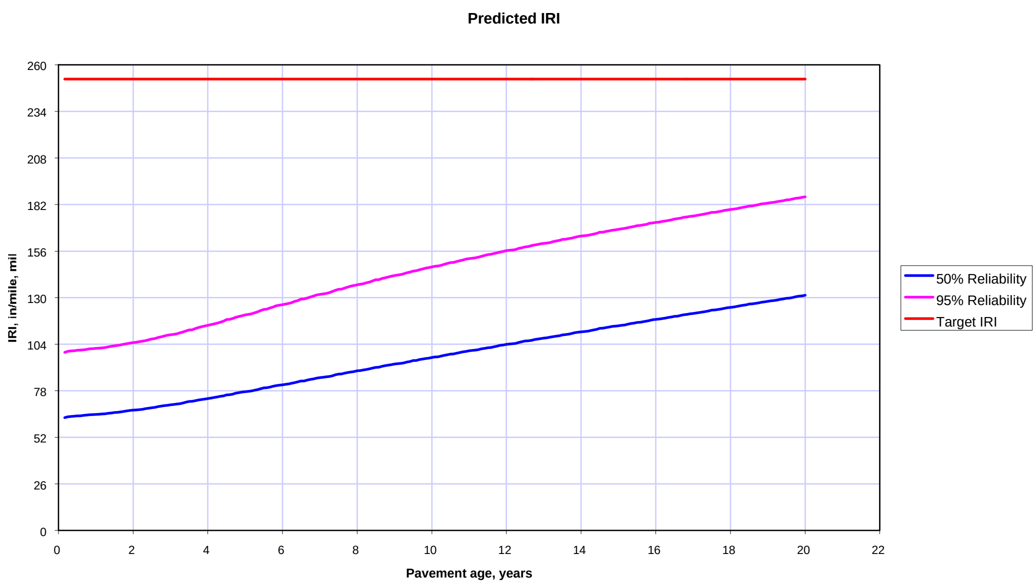

Figure 55. Sample Plot of Predicted IRI at different reliability levels for a given JPCP design (note that this example design meets the 95 percent reliability criteria at 20 years).

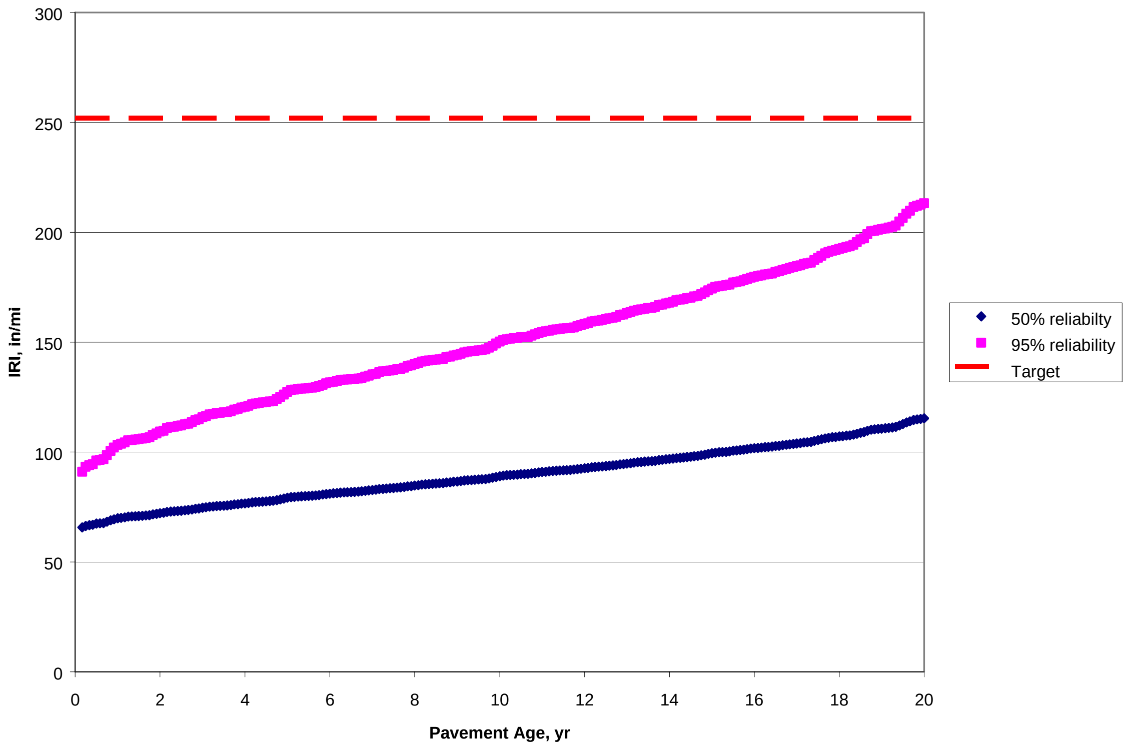

Figure 56. Sample Plot of Predicted IRI at different reliability levels for a given CRCP design (note that this example design meets the 95 percent design reliability criteria at 20 years).