JOINT TRANSPORTATION
RESEARCH PROGRAM
INDIANA DEPARTMENT OF TRANSPORTATION
AND PURDUE UNIVERSITY

COMPREHENSIVE TESTING GUIDELINES TO INCREASE EFFICIENCY IN INDOT OPERATIONS

Seokcheon Lee
Assistant Professor of Industrial Engineering
School of Industrial Engineering
Purdue University
Corresponding Author

Jose Tanchoco
Professor of Industrial Engineering
School of Industrial Engineering
Purdue University

Sang-Phil Kim
Graduate Research Assistant
School of Industrial Engineering
Purdue University

Tommy Nantung
Section Manager
Indiana Department of Transportation

SPR-3401
Report Number: FHWA/IN/JTRP-2012/14
DOI: 10.5703/1288284314977

RECOMMENDED CITATION

Lee, S., J. Tanchoco, S. Kim, and T. Nantung. *Comprehensive Testing Guidelines to Increase Efficiency in INDOT Operations*. Publication FHWA/IN/JTRP-2012/14. Joint Transportation Research Program, Indiana Department of Transportation and Purdue University, West Lafayette, Indiana, 2012. doi: 10.5703/1288284314977.

CORRESPONDING AUTHOR

Seokcheon Lee
School of Industrial Engineering
Purdue University
(765) 494-5419
stonesky@purdue.edu

JOINT TRANSPORTATION RESEARCH PROGRAM

The Joint Transportation Research Program serves as a vehicle for INDOT collaboration with higher education institutions and industry in Indiana to facilitate innovation that results in continuous improvement in the planning, design, construction, operation, management and economic efficiency of the Indiana transportation infrastructure.
https://engineering.purdue.edu/JTRP/index_html

Published reports of the Joint Transportation Research Program are available at: http://docs.lib.purdue.edu/jtrp/

NOTICE

TECHNICAL REPORT STANDARD TITLE PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA/IN/JTRP-2012/14		

4. Title and Subtitle Comprehensive Testing Guidelines to Increase Efficiency in INDOT Operations	5. Report Date August 2012
	6. Performing Organization Code
7. Author(s) Seokcheon Lee, Jose Tanchoco, Sang-Phil Kim, Tommy Nantung	8. Performing Organization Report No. FHWA/IN/JTRP-2012/14
9. Performing Organization Name and Address Joint Transportation Research Program Purdue University 550 Stadium Mall Drive West Lafayette, IN 47907-2051	10. Work Unit No.
	11. Contract or Grant No. SPR-3410
12. Sponsoring Agency Name and Address Indiana Department of Transportation State Office Building 100 North Senate Avenue Indianapolis, IN 46204	13. Type of Report and Period Covered Final Report
	14. Sponsoring Agency Code

15. Supplementary Notes

Prepared in cooperation with the Indiana Department of Transportation and Federal Highway Administration.

16. Abstract

When INDOT designs a pavement project, the decision for QC/QA or non-QC/QA is made solely based on the quantity of pavement materials. However, the actual risk will vary depending on the severity of road conditions. The question is how to differentiate the quality testing efforts according to the severity of road conditions in order to balance required testing resources. We found that the number of commercial vehicles (CV) and heat index (HI: number of hot days/freezing index) can be used as criteria in classifying the road conditions. Using these two criteria, CV and HI, we classify the road sections into four classes and provide different testing guidelines for different classes.

17. Key Words	18. Distribution Statement
QC/QA, performance-based, testing guideline	No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	23	

Form DOT F 1700.7 (8-69)

EXECUTIVE SUMMARY

COMPREHENSIVE TESTING GUIDELINES TO INCREASE EFFICIENCY IN INDOT OPERATIONS

Introduction

When the Indiana Department of Transportation designs a pavement project, a decision for QC/QA (Quality Control/Quality Assurance) or non–QC/QA is made solely based on the quantity of pavement materials to be used in the project. Once the pavement project is designated as QC/QA, quality characteristic values through a certain testing requirement (test types and sample sizes) are obtained and evaluated in comparison with certain testing criteria to ensure that the constructed pavement will meet the pavement design life. In the current INDOT practice of pavement materials testing, a testing requirement (QC/QA or non–QC/QA) is uniformly applied based on pavement quantity, regardless of road condition factors, such as traffic load, climate, and speed limit, that largely affect the pavement lifetime realistically. However, the actual risk will vary depending on the severity of road conditions; severe climate and heavily loaded traffic cause certain roads to fail much earlier than their designated design life, while other roads last much longer. There is an opportunity here to balance required testing resources by differentiating testing requirements for different road conditions. Stricter testing requirements for roads under severe conditions will reduce the error of placing out-of-specification materials in the field. However, since there will be various testing requirements that achieve a certain degree of risk, it is possible to classify road sections for different intensities of testing requirement. For example, a reduced testing requirement (or even non–QC/QA) may suffice for low and middle volume traffic roads as long as the requirement achieves the target risk level.

Findings

Extended regression models were developed for pavement performance prediction and, using the variance of predicted performance, the risks of premature failure were estimated. We found that the number of commercial vehicles and heat index (number of hot days/freezing index) are good indicators for the risk of IRI and Rut, respectively. Using these two indicators, we were able to classify road sections into four groups and found this classification works well in distinguishing risky and safe road sections. The findings show the importance of traffic condition and weather condition on the degradation of pavement performance.

Recommendations for Implementation

In addition to tonnage, INDOT should consider weather and traffic conditions to determine whether the project is assigned as QC/QA or not. The classified four groups have certain risk characteristics:

1. high risks on both of IRI and Rut (H-H);
2. low risk on Rut and high risk on IRI (L-H);
3. high risk on Rut and low risk on IRI (H-L); and
4. low risks on both IRI and Rut (L-L).

Depending on the risk characteristics, the intensity of test requirement can be classified accordingly. For example, since the L-L group has low risk in both IRI and Rut, the size of test sample can be reduced or they can be classified as non–QC/QA. And the H-H group might need to be classified as QC/QA even if the tonnage is less than 5,000 tons. Unfortunately, PCR is not significantly affected by the proposed classification scheme; therefore PCR-related tests should be done as current practice.

Our approach heavily relies on the prediction models for pavement performance. However, the road sections we used in analysis are less than 4 years old, due to the lack of aged data. Therefore, for more reliable results, collecting data for a longer period is desirable. And, the sources of abnormality in performance data should be examined and eliminated. Moreover, if INDOT accumulates performance data according to different testing efforts, it would be possible to quantitatively define the test requirement for each class of road condition.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

In the last 40 years, many State Departments of Transportation have already implemented Quality Control/Quality Assurance (QC/QA) for their pavement projects. When INDOT designs a pavement project, a decision for QC/QA or non–QC/QA is made solely based on the quantity of pavement materials to be used in the project. Once the pavement project is designated as QC/QA, quality characteristic values through a certain testing requirement (test types and sample sizes) are obtained and evaluated in comparison with certain testing criteria, to ensure the constructed pavement will meet the pavement design life. In the current INDOT practice of pavement materials testing, a testing requirement (QC/QA or non–QC/QA) is uniformly applied based on pavement quantity, regardless of road condition factors such as traffic load, climate, and speed limit that largely affect the pavement lifetime realistically.

Variability in the performance of pavement has been recorded since the 1960s during the AASHO Road Test project. Even with well-trained inspectors, well equipped testing labs, competent contractors, and intensive efforts on the part of the owner of the project, it is not possible to eliminate the variability of pavement materials. Therefore, the owner of the project has to assume some acceptable risk in any pavement project. The main purpose of pavement materials testing is to prevent premature pavement failure or, statistically speaking, to limit the risk (probability) of premature failure based on an acceptable level of confidence.

However, the actual risk will vary depending on the severity of road conditions; severe climate and heavily loaded traffic cause certain roads to fail much earlier than their designated design life, while other roads last much longer. There is an opportunity here to balance required testing resources by differentiating testing requirements for different road conditions. Stricter testing requirements for roads under severe conditions will reduce the error of placing out-of-specification materials in the field. However, since there will be various testing requirements that achieve a certain degree of risk, it is possible to classify road sections for different intensities of testing requirement, e.g. a reduced testing requirement (or even non–QC/QA) may suffice for low and middle volume traffic roads as long as the requirement achieves the target risk level.

2. RESEARCH OBJECTIVES

2.1 Problem Definition

Pavement materials specification designation is the issue facing INDOT pavement projects from design to construction. There were, for example, some instances where a US route or State route with low volume traffic had to be assigned QC/QA pavement materials because the quantity of the pavement materials warranted QC/QA materials. With low volume traffic, the risk of premature pavement failure is very small and most of the time the pavement lasts longer than its initial projection. On the other hand, there are some instances where Interstate and US Highways with heavy traffic condition were specified with non–QC/QA pavement materials because the projects did not meet the QC/QA quantity requirement. Such situations increase the risk of premature pavement failure. In some pavement design projects, such as US Highways in urban areas with mostly passenger car traffic, a full blown QC/QA array of testing is not needed for quality assurance. With a reduced testing program, INDOT can assume an acceptable risk while assuring that the pavement will perform as intended.

2.2 Objectives and Expected Benefits

The objective of this project is to develop a comprehensive performance-based classification scheme of testing requirements based on road conditions for HMA pavements that:

- Limit the INDOT risk of premature pavement failure to a certain degree.
- Increase efficiency in testing efforts through better testing programs.
- Reduce total construction costs through efficiency in testing programs.
- Reduce future pavement maintenance and rehabilitation costs by preventing marginal materials in certain classifications of roads (interstate, etc.)
- Shorten the duration of construction projects through more efficient testing programs.
- Reduce the costs of pavement materials by placing appropriate materials in correct designated road classifications.

3. OVERALL RESEARCH PROCEDURE

Figure 3.1 illustrates our overall research procedure. We collected and cleaned pavement performance data (IRI, Rut, and PCR) for HMA. And, contract history,

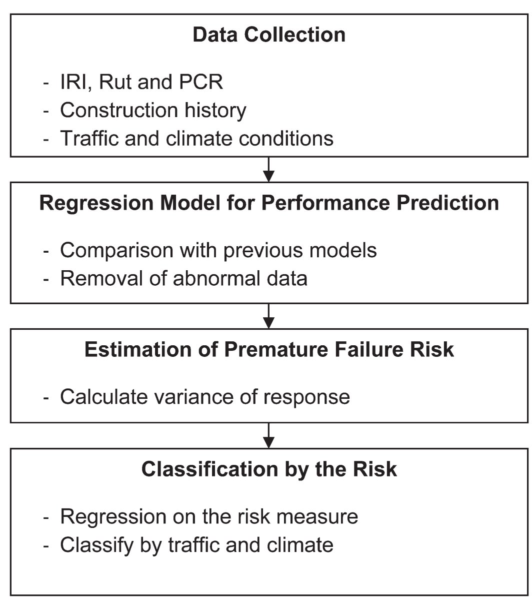

Figure 3.1 Flow chart of research procedure.

traffic and weather data were also obtained. Regression models were developed for performance prediction. And, using the result of regression, we calculated the risk (probability) of premature failure within design life span. According to the risk the road sections could be classified by traffic and weather conditions.

4. RESEARCH RESULTS AND FINDINGS

4.1 Data Collection

The performance (IRI, Rut, and PCR) data for 8 years, from 2002 to 2009, were collected. The data set includes the road type, location, direction, and performance measurements from left and right sides of road and average. To smooth out the noise and to make compact data set, we used average performance of 1 mile instead of 0.1 miles in which the raw data are. The ages of road sections were retrieved using contract history data. Because the contract history data contains only from 2005 to 2010, the oldest road section we have will be 4 years old. We selected HMA resurface cases because they are most common among construction history data.

For traffic data, we collected annual average daily traffic (AADT) and daily average number of commercial vehicles. Speed limits are assumed to be 70, 55 and 45 for Interstate, US route and State route, respectively (in consultation with INDOT engineer due to the unavailability of speed limit database). Weather conditions for each county were collected. The weather data includes the following six weather factors.

1. Average summer temperature
2. Average winter temperature
3. Number of hot days
4. Number of cold days
5. Number of wet days
6. Freezing index

After the preliminary regression analysis, we found that there are many road sections whose pavement performances are indeed improving as they get older; 37%~62% (depending on the interval and road type, refer to Appendix B for more details) of data points show this abnormality. Though this abnormality must be investigated further, it is out of scope of this study. Therefore, we excluded the road sections that contain the abnormal data points.

After we remove the abnormal data, we got 35,457 miles of road sections as described in Table 4.1 and used them for our analysis.

TABLE 4.1
The Numbers of Road Sections (1 mile) Used in the Study

Performances	Interstate	US Route	State Route	Total
IRI	1,182 (7.6%)	4,111 (26.3%)	10,319 (66.1%)	15,612
Rut	158 (0.8%)	438 (2.3%)	18,048 (96.8%)	18,644
PCR	87 (7.2%)	343 (28.6%)	780 (64.9%)	1,201

4.2 Regression Models for Performance Prediction

As aforementioned, we collected three traffic conditions and six weather factors. We built extended regression models for performance prediction, using these nine traffic and weather conditions, and age of road section. The ten main factors are as follows.

1. Age
2. Speed limit
3. AADT
4. Number of commercial vehicles
5. Numbers of wet days
6. Number of hot days
7. Number of cold days
8. Average summer temperature
9. Average winter temperature
10. Freezing index

As a preliminary analysis, we compared our regression models with previous models, Gulen's (*1*) and Ong's (*2*) models (Appendix A). We applied these two previous models to the data (for IRI and Rut) we collected (including the abnormal data points), and compared with our extended models with ten factors as shown in Table 4.2.

Obviously, our extended models outperform the previous models because the extended models consider more factors. However, the goodness levels of fits (R^2) of the extended models are still not good enough for performance prediction models.

In order to improve the regression models, we extended the models even further by adding second order interactions (multiplications of two main factors) besides 10 main factors, 55 factors in total. Fifty-five factors seem too many for a prediction model, but our purpose of regression is to calculate the risk of premature failure and thereby to find a good classification scheme based on the risk. Therefore, we keep those 55 factors for this research.

After including second order interactions and then excluding the road sections with abnormal data points, we could improve our regression models significantly as Table 4.3 shows.

As a result, we found that the linear regression models for Rut and PCR and exponential regression model for IRI are the best fits.

4.3 Estimation of Risk of Premature Failure

What we can get from the regression analysis is not only the best estimation of prediction but also the

TABLE 4.2
Comparison of Goodness of Fit (R^2) of Regression Models

	IRI	Rut
Linear (Gulen's)	0.23%	0.156%
Exponential (Ong's)	0.92%	4.016%
Extended Linear	3.34%	**12.77%**
Extended Exponential	**5.33%**	12.14%

TABLE 4.3
R^2 of Extended Regression Models for Performance Prediction

R^2 for IRI	Linear	Exponential
With interactions	8.1%	10.2%
With interactions + Excluding abnormal sections	12.2%	19.2%
R^2 for Rut	**Linear**	**Exponential**
With interactions	19.1%	19.0%
With interactions + Excluding abnormal sections	34.9%	31.2 %
R^2 for PCR	**Linear**	**Exponential**
With interactions	13.5%	13.6%
With interactions + Excluding abnormal sections	35.4%	34.5 %

variation of prediction. The regression models provide the mean (or maximum likelihood) value of performance. Additionally, using the variance-covariance matrix of coefficients of the regression models, we can also estimate the variance of performance (*3*). One-dimensional example is shown in Figure 4.1, where the red dots indicate the possible values of response (performance in our case) while the line represents the mean of response. Using this mean and variance of performance, the probability (risk) of premature failure can be estimated. (Refer to Appendix D)

Applying 20 years of design life, we define the premature failure as follows (*4*):

- More than 200 in/mi at the end of design life for IRI
- More than 0.4 in at the end of design life for Rut
- Less than 70 points at the end of design life for PCR

And, combining the mean-variance of performance and the premature failure criteria, the risk of premature failure can be calculated. The risk of premature failure was then estimated for each road section.

4.4 Classification of Road Sections by Condition

First, we built another set of regression models on the risk of premature failure, with the same 55 factors

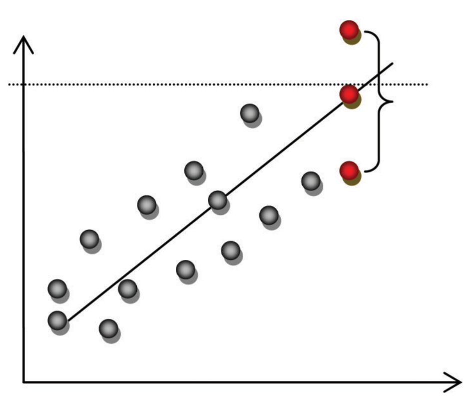

Figure 4.1 Example of response variable in one dimension.

used in the performance prediction modeling, in order to check if the factors we collected can be good predictors on the risk and if so, which factors have greater impact on the risk. The regression results are shown in Table 4.4, confirming that the factors are good predictors on the risk, especially for Rut and PCR.

In order to find the most critical factors, we standardized factors and ran regression again. This standardized regression (*5*) would show the magnitudes of impact of each factor. For all performances, AADT, number of commercial vehicles, number of hot days and freezing index are shown to be the most critical factors (Appendix E).

After several trials, we found that the road conditions can be well classified into four groups by the number of commercial vehicles, number of hot days and freezing index. Indeed, the number of hot days and freezing index tend to be in opposite direction. The higher number of hot days and the lower freezing index mean the road condition in the higher temperature region. Therefore, to reduce the number of factors for classification, we define heat index (HI) as following:

$$Heat\ Index(HI) = \frac{Number\ of\ Hot\ days}{Freezing\ Index}$$

The road section can be classified by the number of commercial vehicles (CV) for IRI, and, for Rut, the heat index can be a good indicator to classify a road section. By trial and error, we found that the critical points are 100 and 0.1 for the number of commercial vehicles and heat index, respectively.

- IRI : By the number of annual commercial vehicles (high > 100, low < 100)
- Rut : By heat index (number of hot days/freezing index, high > 0.1, low < 0.1)

This result is well matched with intuition. High temperature softens asphalt binder, allowing heavy tire loads to deform the pavement into ruts. And, the number of commercial vehicles is more effective than AADT especially on HMA pavement.

Tables 4.5 and 4.6 show the classification of road sections and the mean risk of each class for IRI, Rut and PCR. Unfortunately, we could not find a good indicator for classification in point of view of PCR. More detailed results of this classification can be found in Appendix F.

5. CONCLUSIONS

Extended regression models are developed for pavement performance prediction and, using the variance of

TABLE 4.4
Coefficient of Determination R^2 (Goodness of Fit)

Regression	IRI	Rut	PCR
R^2	26.4%	92.4%	92.3%

TABLE 4.5
Classification of Road Sections by CV and HI

H-H	H-L
High heat index and high number of commercial vehicles	High heat index and low number of commercial vehicles
L-H	**L-L**
Low heat index and high number of commercial vehicles	Low heat index and low number of commercial vehicles

TABLE 4.6
Mean Risk of Each Class

H-H	H-L
Mean risk of IRI: 98.3% Mean risk of Rut: 98.8% Mean risk of PCR: 27.7%	Mean risk of IRI: 34.1% Mean risk of Rut: 87.3% Mean risk of PCR: 43.8%
L-H	**L-L**
Mean risk of IRI: 98.0% Mean risk of Rut: 8.8% Mean risk of PCR: 33.9%	Mean risk of IRI: 16.3% Mean risk of Rut: 1.08% Mean risk of PCR: 27.2%

predicted performance, the risks of premature failure are estimated. We found that the number of commercial vehicles and heat index (number of hot days/freezing index) are good indicators for the risk of IRI and Rut, respectively. Using these two indicators, we could classify road sections into four groups and found this classification works well in distinguishing risky and safe road sections. This shows the importance of traffic condition and weather condition on the degradation of pavement performance.

6. RECOMMENDATIONS FOR IMPLEMENTATION

In addition to tonnage, INDOT should consider weather and traffic conditions to determine whether a project is assigned as QC/QA or not. Since the L-L group has low risk in both IRI and Rut, the size of test sample can be reduced or they can be classified as non–QC/QA. And H-H group might need to be classified as QC/QA even if the tonnage is less than 5,000 tons.

In between, H-L and L-H classes have medium level of severity. As Table 6.1 shows, L-H class has high risk on IRI, therefore, it would have intensive (regular testing) requirement of IRI related tests. And L-H class might have moderate (reduced testing) requirement of Rut related tests since this class has very low risk on Rut. And, similarly, H-L class should have intensive

TABLE 6.1
Intensity of Testing Requirement by Class

H-H	H-L
IRI related test: Intensive Rut related test: Intensive	IRI related test: Moderate Rut related test: Intensive
L-H	**L-L**
IRI related test: Intensive Rut related test: Moderate	IRI related test: Moderate Rut related test: Moderate

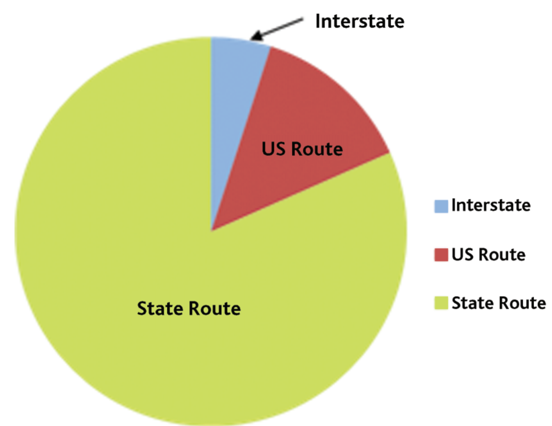

Figure 6.1 Proportion of road types in data.

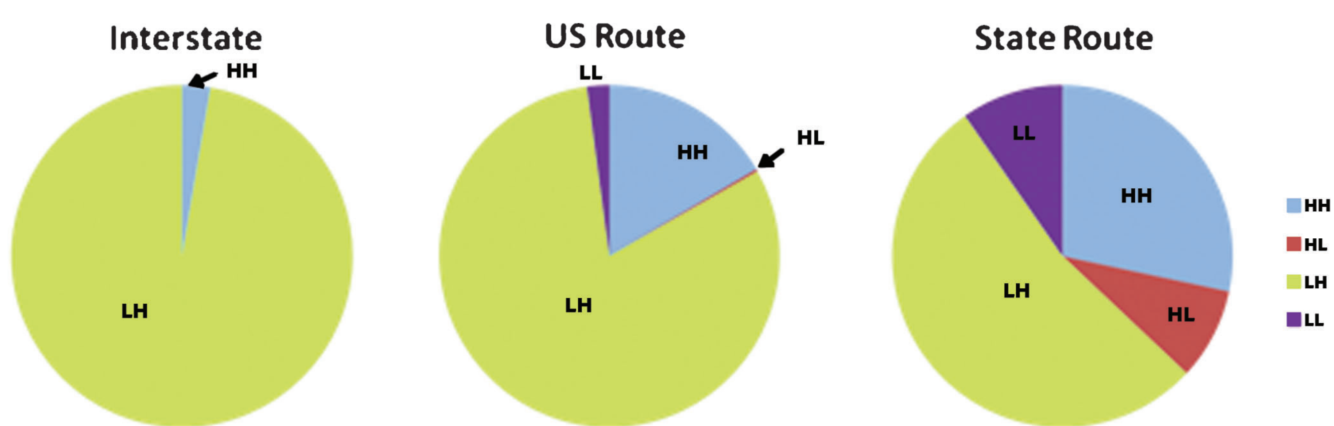

Figure 6.2 Proportion of classes of each road type.

requirement of Rut related tests and might have moderate testing requirement for IRI. The combinations are described in Table 6.1. Unfortunately, PCR is not significantly affected by the proposed classification scheme; therefore PCR related tests should be done as current practice.

More than three quarters of data collected are State routes as Figure 6.1, and as Figure 6.2 shows, most of road sections fall into class L-H. Therefore, there should be an opportunity to achieve a more efficient way of managing testing force by reallocation. INDOT may reallocate some portion of testing efforts from the projects of class L-H into those of class H-H.

Our approach heavily relies on the prediction models for pavement performance. However, the road sections we used in analysis are less than 4 years-old, due to the lack of aged data. Therefore, for more reliable results, collecting longer period data is desirable. And, the sources of abnormality in performance data should be examined and eliminated. Moreover, if INDOT accumulates performance data according to different testing efforts, it would be possible to quantitatively define the test requirement for each class of road condition.

REFERENCES

1. Gulen, S., K. Zhu, J. Weaver, J. Shan, and W. F. Flora. *Development of Improved Pavement Performance Prediction Models for the Indiana Pavement Management System.* Publication FHWA/IN/JTRP-2001/17. Joint Transportation Research Program, Indiana Department of Transportation and Purdue University, West Lafayette, Indiana, 2001. doi: 10.5703/1288284313192.
2. Ong, G., T. E. Nantung, and K. C. Sinha. *Indiana Pavement Preservation Program*. Publication FHWA/IN/JTRP-2010/14. Joint Transportation Research Program, Indiana Department of Transportation and Purdue University, West Lafayette, Indiana, 2010. doi:10.5703/1288284314258.
3. Kutner, M., C. Nachtsheim, and J. Neter. *Applied Linear Statistical Models*. 4th ed. McGraw-Hill/Irwin, New York, 2004.
4. ARA, Inc., ERES Consultants Division. Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, Part 3—Design Analysis. In *Design of New and Reconstructed Flexible Pavements*. National Cooperative Highway Research Program, Transportation Research Board of the National Academies, Washington, D.C., 2004.
5. Bring, J. How to Standardize Regression Coefficients. *The American Statistician*, Vol. 48, 3, 1994, pp. 209–213.

APPENDIX A

PREVIOUS PREDICTION MODELS

1. Linear Model

Gulen's model (*1*) is a linear regression model to predict IRI and Rut by age and AADT as follows.

$$IRI(or\ Rut) = \beta_0 + \beta_1\ AGE + \beta_2\ AADT$$

2. Exponential Model

Ong's model (*2*) is an exponential regression model to predict IRI and Rut by interactions between AGE, AADT and Freezing Index (FRZINX) as follows..

$$IRI(or Rut) = Exp(\beta_0 + \beta_1\ \mathrm{AADT} \times AGE + \beta_2\ FRZINX \times AGE)$$

We applied these two models to the data we collected, and compared them with our extended models which have total 55 factors (Refer to Appendix C) that include ten main factors and their second order interactions. Obviously, our extended models outperform over the previous models because the extended models consider more factors. However, the goodness levels of fits (R^2) of the extended models are still not good enough for performance prediction models. We need to improve the regression models (see Appendices B and C).

TABLE A.1
Comparison of Goodness of Fit (R^2) of Regression Models

	IRI	Rut
Linear (Gulen's)	0.23%	0.156%
Exponential (Ong's)	0.92%	4.016%
Extended Linear	3.34%	**12.77%**
Extended Exponential	**5.33%**	12.14%

APPENDIX B

ABNORMAL PERFORMANCE DATA

Table B.1 shows the portion of abnormal data, obtained by comparing IRI data of two consecutive years. If the pavement performance is decreasing, it means the roughness gets improved. Therefore, the data from the road section is considered abnormal.

Table B.2 shows the portion of abnormal data when the performances are compared in two years interval.

Table B.3 shows the portion of abnormal data when the performances are compared in three years interval.

We couldn't find any specific tendency of the abnormality, i.e. the abnormality exists uniformly in all road types and in all years. Although it is out of scope of this research, this problem must be examined further to improve the quality of the pavement performance measurement system.

TABLE B.1
Proportion of Abnormal Data in One Year Interval (IRI)

	'05–'06			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	1178	3225	5765	**10168**
Increase	565	1985	3601	**6151**
Total	1743	5210	9366	**16319**
Abnormal	67.6%	61.9%	61.6%	**62.3%**
Normal	32.4%	38.1%	38.4%	**37.7%**

	'06–'07			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	407	926	2332	**3665**
Increase	91	1440	3144	**4675**
Total	498	2366	5476	**8340**
Abnormal	81.7%	39.1%	42.6%	**43.9%**
Normal	18.3%	60.9%	57.4%	**56.1%**

	'07–'08			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	778	2077	3798	**6653**
Increase	594	1888	3684	**6166**
Total	1372	3965	7482	**12819**
Abnormal	56.7%	52.4%	50.8%	**51.9%**
Normal	43.3%	47.6%	49.2%	**48.1%**

	'08–'09			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	75	274	675	**1024**
Increase	77	417	1073	**1567**
Total	152	691	1748	**2591**
Abnormal	49.3%	39.7%	38.6%	**39.5%**
Normal	50.7%	60.3%	61.4%	**60.5%**

TABLE B.2
Proportion of Abnormal Data in Two Years Interval (IRI)

	'05–'07			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	886	2392	3617	**6895**
Increase	418	1192	2767	**4377**
Total	1304	3584	6384	**11272**
Decrease	67.9%	66.7%	56.7%	**61.2%**
Normal	32.1%	33.3%	43.3%	**38.8%**

	'06–'08			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	256	920	2126	**3302**
Increase	339	1585	3457	**5381**
Total	595	2505	5583	**8683**
Decrease	43.0%	36.7%	38.1%	**38.0%**
Normal	57.0%	63.3%	61.9%	**62.0%**

	'07–'09			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	66	276	632	**974**
Increase	86	415	999	**1500**
Total	152	691	1631	**2474**
Decrease	43.4%	39.9%	38.7%	**39.4%**
Normal	56.6%	60.1%	61.3%	**60.6%**

TABLE B.3
Proportion of Abnormal Data in Three Years Interval

	'05–'08			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	248	850	2213	**3311**
Increase	195	1003	1981	**3179**
Total	443	1853	4194	**6490**
Decrease	56.0%	45.9%	52.8%	**51.0%**
Normal	44.0%	54.1%	47.2%	**49.0%**

	'06–'09			
	Interstate	**US Route**	**State Route**	**Total**
Decrease	64	209	688	**961**
Increase	88	482	1060	**1630**
Total	152	691	1748	**2591**
Decrease	42.1%	30.2%	39.4%	**37.1%**
Normal	57.9%	69.8%	60.6%	**62.9%**

APPENDIX C

EXTENDED REGRESSION MODELS

We extended the previous regression models for performance prediction by including more road condition factors and their interactions.

- Road characteristics: Age; speed limit
- Traffic conditions: AADT; number of commercial vehicles
- Climate conditions: Numbers of wet days, hot days, and cold days in a year; average summer and winter temperatures; freezing index

Using these ten factors and all second order interactions (multiplications of two factors), a regression analysis has been conducted as shown in Tables C.1 and C.2. There are significant improvements in R^2 in comparison with previous models, achieving 19.2% for IRI, 34. 9% for Rut, and 35.4% for PCR.

TABLE **C.1**
Improving R^2 of Regression Models

R^2 for IRI	Linear	Exponential
Extended model	3.3%	5.3%
With interactions	8.1%	10.2%
Excluding Abnormal sections	12.2%	**19.2%**
R^2 for Rut	**Linear**	**Exponential**
Extended model	12.8%	12.1%
With interactions	19.1%	19.0%
Excluding Abnormal sections	**34. 9%**	31.2 %
R^2 for PCR	**Linear**	**Exponential**
With interactions	13.5%	13.6%
Excluding Abnormal sections	35.4%	34.5 %

TABLE **C.2**
Coefficients of Regression Models

	IRI		Rut		PCR	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Intercept	−18.76	0.708	−61.73	0	−4355	0.02
age	−0.2366	0.596	−1.17419	0	137.76	0
AADT	8.77E–05	0.392	−3.20E−04	0	−8.71E–03	0.048
speed	−1.1682	0	−0.00269	0.966	16.811	0.001
CommVeh	7.07E-05	0.854	1.11E-03	0	2.13E-02	0.267
wetdays	0.5587	0	0.28587	0	16.473	0.001
wintemp	0.084	0.941	1.1032	0	48.62	0.226
sumtemp	−1.2415	0.062	0.237	0.171	57.37	0.026
hotdays	2.3229	0	0.62508	0	4.038	0.631
coldays	0.9486	0	0.34247	0	1.44	0.816
frz_index	−4.70E-05	0.996	7.06E-03	0.001	5.85E-01	0.103
age * AADT	5.30E-07	0.368	1.14E-06	0	5.24E-06	0.892
age * speed	0.001924	0.017	0.000589	0	0.0000439	0.8
age * CommVeh	5.30E-06	0.039	6.94E-06	0.001	2.49E-01	0
age * wetdays	7.43E-05	0.894	−4.80E-04	0	1.46E-03	0.972
age * wintemp	−0.01346	0.006	−1.38E-03	0.295	−4.00E-02	0.928
age * sumtemp	0.010277	0.086	0.016833	0	−1.8889	0
age * hotdays	−0.00275	0.001	−0.000066	0.742	0.07791	0.249
age * coldays	−0.00111	0.088	0.000253	0.112	−0.11781	0.038
age * frz_index	−0.00018	0	0.0000672	0	−0.00179	0.607
AADT * speed	2.30E-07	0.03	−2.50E-07	0	2.00E-08	0.001
AADT * CommVeh	0	0	0.00E+00	0	−8.89E-06	0.048
AADT * wetdays	1.30E–07	0.391	−8.00E-08	0.022	2.21E-05	0
AADT * wintemp	−5.90E-06	0	−2.30E-06	0	−8.36E-05	0.082
AADT * sumtemp	1.18E-06	0.424	5.66E-06	0	1.13E-04	0.052
AADT * hotdays	1.11E-06	0	−1.00E-08	0.909	2.48E-05	0.009
AADT * coldays	−0.0000011	0	−1.40E-07	0	−1.53E-06	0.783
AADT * frz_index	6.00E-08	0	2.00E-08	0	2.90E-07	0.372
speed * CommVeh	3.90E-06	0	−9.70E-07	0	2.50E-07	0.988
speed * wetdays	0.000556	0.001	−3.40E-04	0.007	−9.26E-05	0
speed * wintemp	0.000124	0.934	−0.00298	0	0.0003383	0.207
speed * sumtemp	0.013438	0	0.002247	0.015	−0.0002856	0.216
speed * hotdays	0.001205	0	−0.00048	0.002	−0.0000487	0.238
speed * coldays	0.000474	0.012	−0.00012	0.123	0.00002761	0.41
speed * frz_index	8.90E-05	0	−0.00001	0.209	−0.00000036	0.797
CommVeh * wetdays	1.33E-06	0.005	1.43E-06	0	−9.56E-04	0.899
CommVeh * wintemp	2.96E-05	0	1.39E-05	0	−1.46E-01	0.022
CommVeh * sumtemp	−1.90E-05	0	−2.30E-05	0	−1.35E-01	0.036
CommVeh * hotdays	−6.10E-06	0	1.80E-07	0.676	−1.46E-02	0.222
CommVeh * coldays	4.90E-06	0	1.76E-06	0	−3.10E-02	0
CommVeh * frz_index	−3.10E-07	0	0.00000016	0	−0.0004958	0.321
wetdays * wintemp	−0.02395	0	−5.80E-03	0	6.56E-02	0.419
wetdays * sumtemp	0.006311	0	−0.00054	0.033	−0.24229	0
wetdays * hotdays	−0.00069	0	−0.00016	0	−0.010472	0.052
wetdays * coldays	−0.00528	0	−0.00078	0	−0.00211	0.86
wetdays * frz_index	7.14E-05	0	−0.00001658	0	−0.0006215	0.098
wintemp * sumtemp	0.03155	0.03	−6.40E-04	0.864	−6.50E-01	0.215
wintemp * hotdays	−0.01145	0	−0.0064	0	0.0129	0.935
wintemp * coldays	0.011187	0	0.000609	0	0.00722	0.824
wintemp * frz_index	−0.00018	0.136	−0.00026399	0	−0.007434	0.144
sumtemp * hotdays	−0.02097	0	−0.00443	0	−0.0341	0.74
sumtemp * coldays	−0.00673	0.007	−0.003	0	0.00824	0.922
sumtemp * frz_index	−0.00013	0.269	0.00008175	0.002	−0.003642	0.376
hotdays * coldays	−0.00691	0	−0.00103	0	−0.00676	0.755
hotdays * frz_index	0.000127	0	−0.00001602	0	0.000529	0.279
coldays * frz_index	−0.000016	0.407	−0.0000407	0	−0.0004567	0.568

APPENDIX D

RISK OF PREMATURE Fs

Regression analysis is a widely used statistical tool for prediction. The typical linear regression model can be expressed as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon_i (1 \leq i \leq N),$$

where Y_i is ith observed response (pavement performance in this study), X_{ij} jth factor in ith observation, N the number of observations, and p the number of factors. In matrix form, the model would be:

$$Y = X^{'}\beta + \epsilon.$$

Using the coefficients matrix β, we can calculate the best estimate of mean response $\hat{Y}_h$ for a new observation h as follows:

$$\hat{Y} = X_h^i \beta$$

And, the variance of the response is also estimated, which is not provided by commercial statistical tools such as Excel:

$$\sigma^2 \left[\hat{Y} \right] = \sigma^2 \left[X_h^{'} (X^{'} X)^{-1} X_h \right] = X_h^{'} \sigma^2 [B] \, X_h \,,$$

where B is the covariance matrix of coefficients. Once we get the variance of response we can estimate the distribution of real response. Furthermore, the probability that the response is greater than a certain number can be estimated when the distribution of response is assumed to be a normal distribution.

Our regression model has ten main factors and their second order interactions. Therefore, it is impossible to draw the regression model in a two-dimensional graph, but when we draw the model as if it is one factor model, the graph would be like Figure D.1. The blue shaded area represents the probability that the pavement performance (IRI, Rut or PCR) is greater than the limit (red dotted line). We use this probability as the risk measure of premature failure. To find the risk, we use 20 years as the design life.

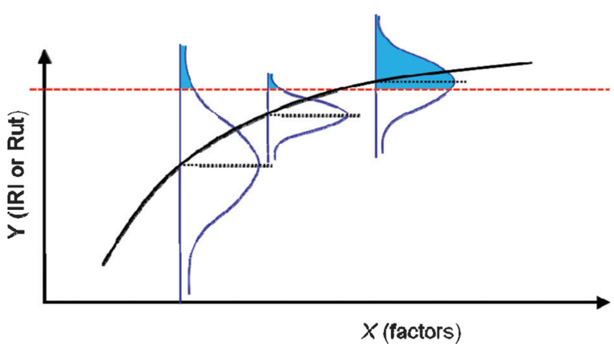

Figure D.1 Estimated risk of premature failure.

APPENDIX E

REGRESSION ON THE RISK OF PREMATURE FAILURE

By using the estimated variance of pavement performance, we calculated the risk of premature failure for each observation and conducted linear regression on the risk instead of pavement performance using the same factors involved in the performance models. The regression models for predicting the risk of premature failure are working well with R^2 26.4% for IRI, 92.4% for Rut, and 92.3% for PCR, confirming that the factors are good predictors on the risk, especially for Rut and PCR.

Table E.1 shows the regression coefficients of factors for IRI, Rut and PCR. The results of the regular regression show the best estimation of coefficient of each factor. However, when the factors have different scales and ranges, it is difficult to see which factor has higher impact on the response. In order to see the impact of factors, regression has been conducted after all the factors are standardized. Table E.2 shows the ranked list of factors based on standardized regression coefficients. Higher ranked factor has higher impact on the risk of premature failure.

TABLE E.1
Regression Coefficients on Risk Measure

Factors	IRI	Rut	PCR
Intercept	87.7	36	33.1
AADT	58.3	−674.1	−1155.6
CommVeh	256.7	504.4	1194
Speed	191.4	−132	−466.6
WetDays	83.7	448.6	−663.4
Avg WinTemp	−94.4	403.2	1206.5
Avg SumTemp	76.0	275.3	−25.9
Hot Days	879.3	1757.2	−1566.7
Cold Days	−136.0	−417.8	1052.2
Frz Idx	993.9	2445.1	−958.8
AADT * CommVeh	−59.8	−0.3	2.8
AADT * Speed	7.1	21.7	−25.1
AADT * WetDays	34.5	−24.3	153.8
AADT * Avg WinTemp	−53.6	−294.3	−213.6
AADT * Avg SumTemp	−8.8	1036.4	1243.2
AADT * Hot Days	13.4	−37.6	14.5
AADT * Cold Days	43.7	11.1	−50.4
AADT * Frz Idx	−37.5	−39.1	24.2
CommVeh * Speed	−58.1	−7.7	33.3
CommVeh * WetDays	−49.3	26.1	−195.3
CommVeh * Avg WinTemp	5.8	92.9	130
CommVeh * Avg SumTemp	−119.4	−593.6	−1133.7
CommVeh * Hot Days	−58.9	2.4	−10.1
CommVeh * Cold Days	6.4	−33.6	−3.2
CommVeh * Frz Idx	−66.5	1.3	−5.4
Speed * WetDays	−4.0	137.5	126.1
Speed * Avg WinTemp	−5.9	−2.3	−22.3
Speed * Avg SumTemp	−183.5	−14.9	341.7
Speed * Hot Days	19.1	72	74.7
Speed * Cold Days	−69.9	−1.9	64.3
Speed * Frz Idx	45.2	−49.8	2.3
WetDays * Avg WinTemp	−21.3	20.2	−7.5
WetDays * Avg SumTemp	−1.7	−407.4	526.8
WetDays * Hot Days	−51.9	−91.1	−32.7
WetDays * Cold Days	−47.7	−0.4	78.7
WetDays * Frz Idx	−23.1	−325.3	−24.3
Avg WinTemp * Avg SumTemp	86.4	−439.5	−1388.6
Avg WinTemp * Hot Days	30.8	123.6	−35.5
Avg WinTemp * Cold Days	53.8	−146.2	131.9
Avg WinTemp * Frz Idx	55.8	127.7	−451.4
Avg SumTemp * Hot Days	−742.4	−1780.9	1562
Avg SumTemp * Cold Days	141.0	637	−1246.7
Avg SumTemp * Frz Idx	−968.5	−2013.2	1397.4
Hot Days * Cold Days	−64.8	−18.1	10.6
Hot Days * Frz Idx	19.6	−59.6	18.6
Cold Days * Frz Idx	−7.7	−116	−57.2

TABLE E.2
Rankings of Coefficients in Standardized Regression

Rank	IRI	RUT	PCR
1	Frz Idx	Frz Idx	Hot Days
2	Avg SumTemp * Frz Idx	Avg SumTemp * Frz Idx	Avg SumTemp * Hot Days
3	Hot Days	Avg SumTemp * Hot Days	Avg SumTemp * Frz Idx
4	Avg SumTemp * Hot Days	Hot Days	Avg WinTemp * Avg SumTemp
5	CommVeh	AADT * Avg SumTemp	Avg SumTemp * Cold Days
6	Speed	AADT	AADT * Avg SumTemp
7	Speed * Avg SumTemp	Avg SumTemp * Cold Days	Avg WinTemp
8	Avg SumTemp * Cold Days	CommVeh * Avg SumTemp	CommVeh
9	Cold Days	CommVeh	AADT
10	CommVeh * Avg SumTemp	WetDays	CommVeh * Avg SumTemp
11	Avg WinTemp	Avg WinTemp * Avg SumTemp	Cold Days
12	Intercept	Cold Days	Frz Idx
13	Avg WinTemp * Avg SumTemp	WetDays * Avg SumTemp	WetDays
14	WetDays	Avg WinTemp	WetDays * Avg SumTemp
15	Avg SumTemp	WetDays * Frz Idx	Speed
16	Speed * Cold Days	AADT * Avg WinTemp	Avg WinTemp * Frz Idx
17	CommVeh * Frz Idx	Avg SumTemp	Speed * Avg SumTemp
18	Hot Days * Cold Days	Avg WinTemp * Cold Days	AADT * Avg WinTemp
19	AADT * CommVeh	Speed * WetDays	CommVeh * WetDays
20	CommVeh * Hot Days	Speed	AADT * WetDays
21	AADT	Avg WinTemp * Frz Idx	Avg WinTemp * Cold Days
22	CommVeh * Speed	Avg WinTemp * Hot Days	CommVeh * Avg WinTemp
23	Avg WinTemp * Frz Idx	Cold Days * Frz Idx	Speed * WetDays
24	Avg WinTemp * Cold Days	CommVeh * Avg WinTemp	WetDays * Cold Days
25	AADT * Avg WinTemp	WetDays * Hot Days	Speed * Hot Days
26	WetDays * Hot Days	Speed * Hot Days	Speed * Cold Days
27	CommVeh * WetDays	Hot Days * Frz Idx	Cold Days * Frz Idx
28	WetDays * Cold Days	Speed * Frz Idx	AADT * Cold Days
29	Speed * Frz Idx	AADT * Frz Idx	Avg WinTemp * Hot Days
30	AADT * Cold Days	AADT * Hot Days	CommVeh * Speed
31	AADT * Frz Idx	Intercept	Intercept
32	AADT * WetDays	CommVeh * Cold Days	WetDays * Hot Days
33	Avg WinTemp * Hot Days	CommVeh * WetDays	Avg SumTemp
34	WetDays * Frz Idx	AADT * WetDays	AADT * Speed
35	WetDays * Avg WinTemp	AADT * Speed	WetDays * Frz Idx
36	Hot Days * Frz Idx	WetDays * Avg WinTemp	AADT * Frz Idx
37	Speed * Hot Days	Hot Days * Cold Days	Speed * Avg WinTemp
38	AADT * Hot Days	Speed * Avg SumTemp	Hot Days * Frz Idx
39	AADT * Avg SumTemp	AADT * Cold Days	AADT * Hot Days
40	Cold Days * Frz Idx	CommVeh * Speed	Hot Days * Cold Days
41	AADT * Speed	CommVeh * Hot Days	CommVeh * Hot Days
42	CommVeh * Cold Days	Speed * Avg WinTemp	WetDays * Avg WinTemp
43	Speed * Avg WinTemp	Speed * Cold Days	CommVeh * Frz Idx
44	CommVeh * Avg WinTemp	CommVeh * Frz Idx	CommVeh * Cold Days
45	Speed * WetDays	WetDays * Cold Days	AADT * CommVeh
46	WetDays * Avg SumTemp	AADT * CommVeh	Speed * Frz Idx

APPENDIX F

CLASSIFICATION OF ROAD SECTIONS

To accomplish the goal of this research, we need to classify the road sections by their attributes such that the classification should be able to distinguish the risk of premature failure. We found that heat index (number of hot days divided by freezing index) and the number of commercial vehicles are good attributes for the purpose of classification. Therefore, we divide the whole road sections into four groups, High-High, High-Low, Low-High, and Low-Low (level of heat index – level of the number of commercial vehicles). The critical points are 0.1 and 100 for heat index and the number of commercial vehicles, respectively.

Tables F.1, F.2 and F.3 show the descriptive statistics of each group for IRI, Rut and PCR. The CV and HI represent the number of Commercial Vehicle and Heat Index, respectively. Risky road section means that the road section has the risk of premature failure higher than 20%. Figure F.1, Figure F.2 and Figure F.3 show the distributions of risk for each class. It is easier to see how the classification divides the road sections by the risk. As one can see in these figures, road sections for Rut are well classified by heat index but not by the number of commercial vehicles. And, road sections for IRI are well classified by the number of commercial vehicles but not by heat index. And, unfortunately, we could not find a good classification for PCR.

TABLE F.1
Descriptive Statistics of Each Class for IRI

Statistics	High-CV	Low-CV	
Number of sections % of risky sections Mean risk	2495 100% 98.26%	798 51% 34.08%	High-HI
Number of sections % of risky sections Mean risk	5131 100% 98.04%	508 19.50% 16.31%	Low-HI

TABLE F.2
Descriptive Statistics of Each Class for Rut

Statistics	High-CV	Low-CV	
Number of sections % of risky sections Mean risk	2686 100% 98.77%	1216 89.30% 87.34%	High-HI
Number of sections % of risky sections Mean risk	6943 13.50% 8.83%	1178 2% 1.08%	Low-HI

TABLE F.3
Descriptive Statistics of Each Class for PCR

Statistics	High-CV	Low-CV	
Number of sections % of risky sections Mean risk	207 42% 27.7%	96 65% 43.8%	High-HI
Number of sections % of risky sections Mean risk	447 54% 33.9%	46 31% 27.2%	Low-HI

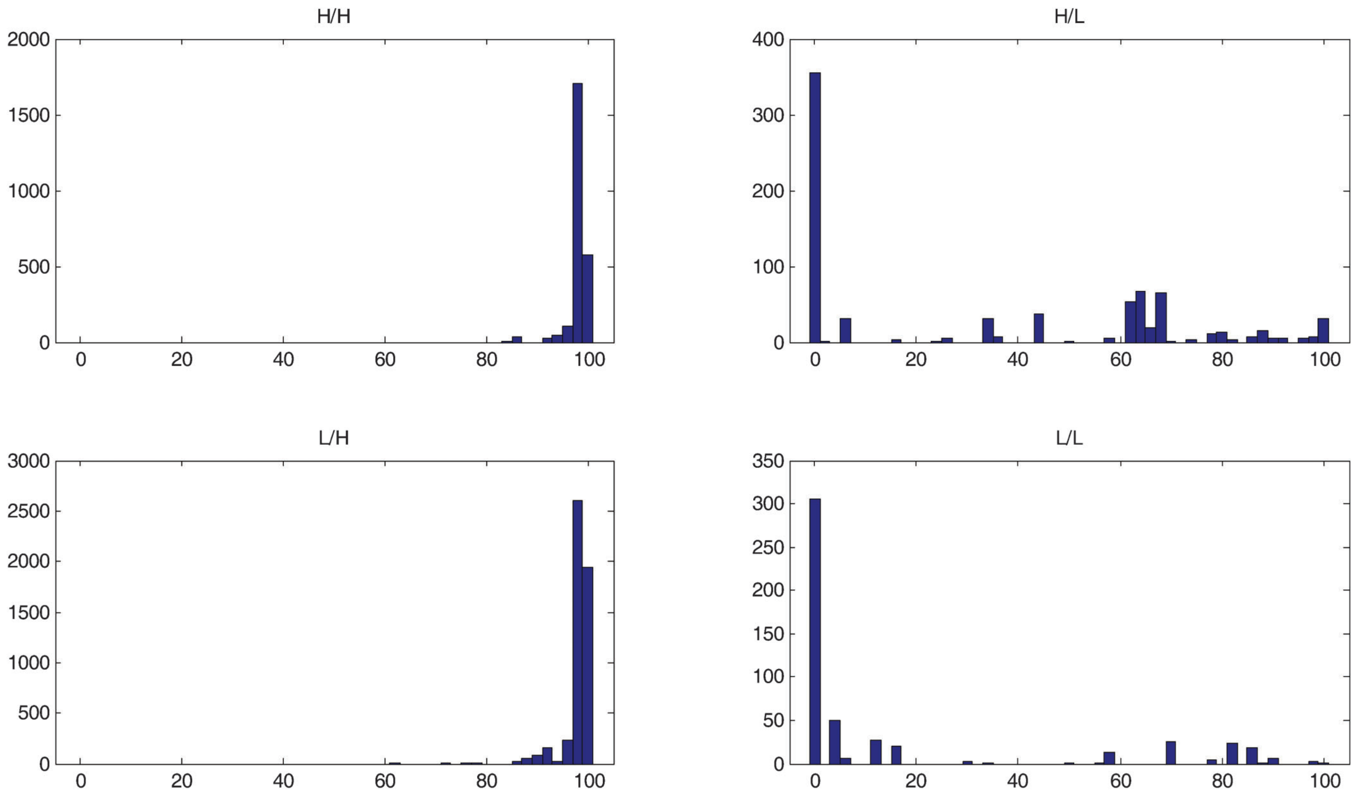

Figure F.1 Risk distributions of each class for IRI (x: risk %, y: # of road sections).

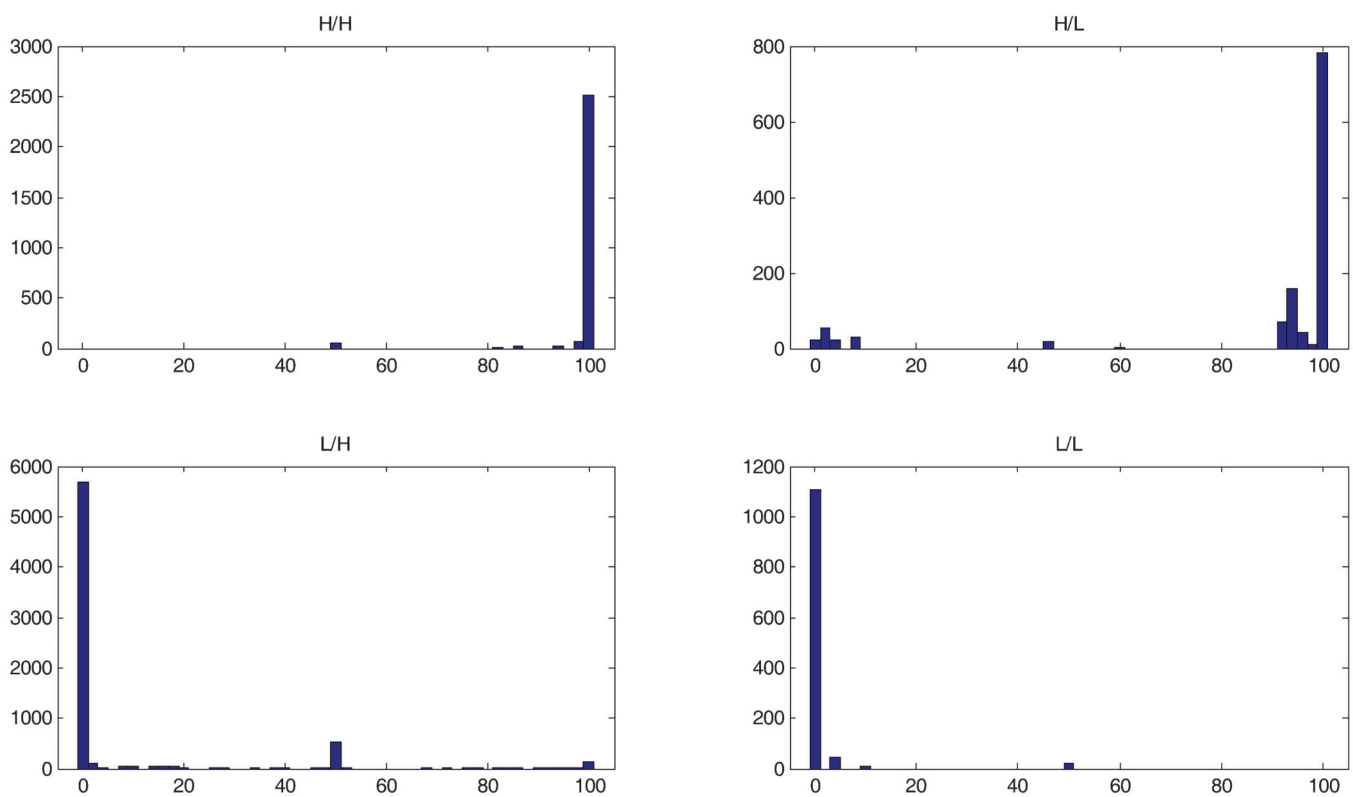

Figure F.2 Risk distributions of each class for Rut (x: risk %, y: # of road sections).

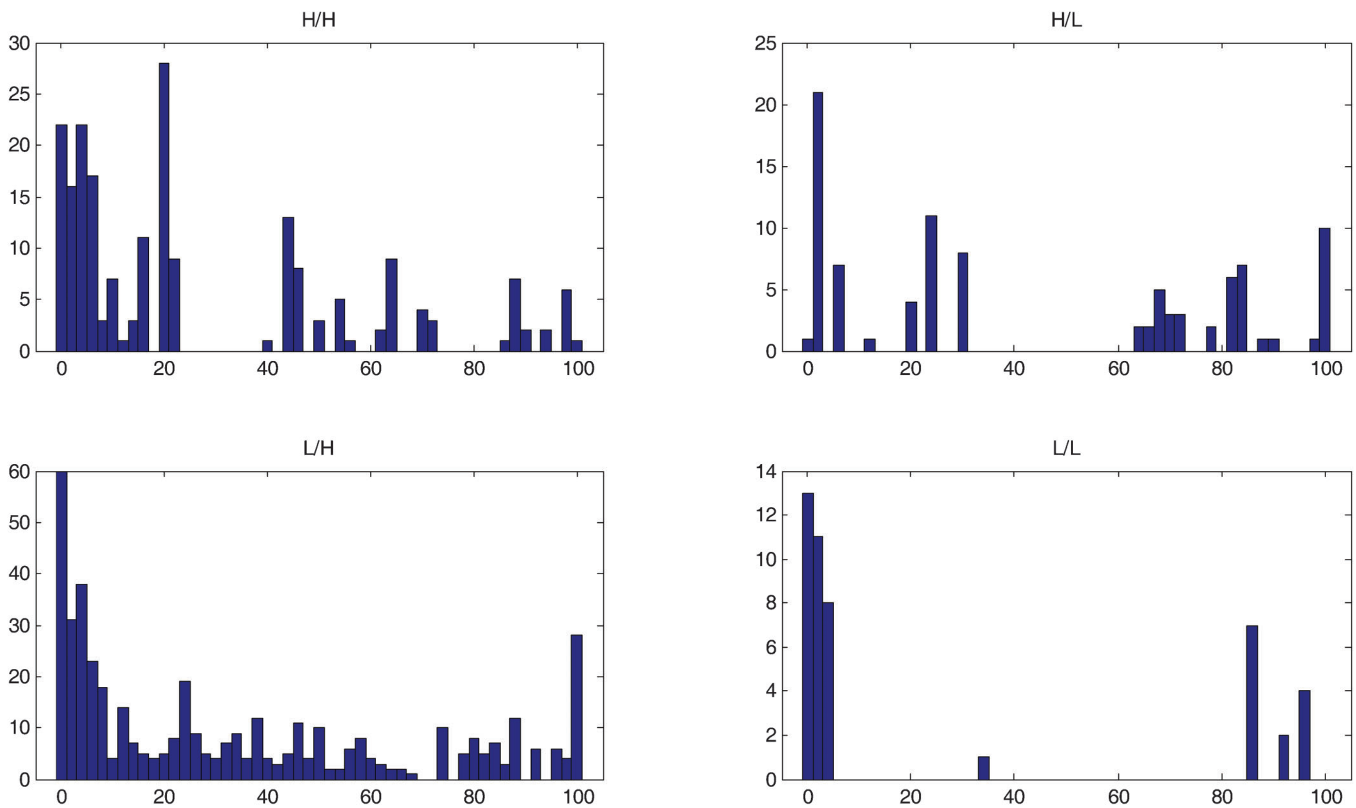

Figure F.3 Risk distributions of each class for PCR (x: risk %, y: # of road sections).