ABSTRACT

Title of Dissertation: A SYSTEMATIC METHODOLOGY FOR EVALUATING AND BALANCING ACCEPTANCE RISKS WITH PAY FACTORS FOR HIGHWAY CONSTRUCTION MATERIALS

Degree candidate: Sahand Karimi

Degree and year: Doctor of Philosophy, 2021

Thesis directed by: Professor Dimitrios G. Goulias
Department of Civil and Environmental Engineering

Over the years the role of State Transportation agencies has shifted from monitoring contractor's quality control of materials and placement techniques to quality assurance and acceptance. This shift has placed more responsibility on the contractor, the producer and the supplier. On the other hand, agency's role has been focusing towards assurance of material quality and sporadic oversight of contractor quality control operations. This shift eventually allows higher level of innovation and flexibility from the contractor, and lower involvement and resources from the agency. To adapt, many agencies have begun revising their acceptance procedures and the development of performance specifications for highway materials. With such transition there is a need to evaluate acceptance risks and balance pay factors based on the performance of the material. Through this process it is important to consider the risks associated with such criteria to both the agency and the supplier. Thus, the objective of this study was to develop a systematic methodology for: (i) evaluating acceptance risks, (ii) balancing agency and contractor risks by adjusting specification acceptance criteria, and (iii) defining a rational approach for balancing pay

rewards to performance and acceptance risks. To demonstrate the effectiveness of the proposed methodology Hot-Mix Asphalt (HMA) was used as an example. Simulation was used for assessing the risks associated with accepting lower quality and rejecting high quality HMA lots. Risk analyses were based on assessing acceptance risks based on performance related properties of the material (e.g., Dynamic Modulus, E*). Operating Characteristic (OC) curves were then used to estimate Type I and Type II risks. OC curves were then used to reassign desired levels of Type I and Type II risks in order to balance the risk levels and examine the impact on specification criteria. Predicted performance and pay factors were then used in assessing and balancing pay factors to acceptance risks based on quality of production. The proposed methodology aids in quantifying acceptance risks for highway materials based on production quality, provides the means for balancing the risks between agency and contractors, and identifies the process for rewarding reasonable pay factors for construction quality in similar materials.

A SYSTEMATIC METHODOLOGY FOR EVALUATING AND BALANCING ACCEPTANCE RISKS WITH PAY FACTORS FOR HIGHWAY CONSTRUCTION MATERIALS

by

Sahand Karimi

Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, College Park in partial fulfillment of the requirements of the degree of Doctor of Philosophy 2021

Advisory Committee:

Professor Dimitrios Goulias, Chair
Professor Sherif Aggour
Professor Ahmet Aydilek
Professor Qingbin Cui
Professor Sung Lee, Dean's Representative

ACKNOWLEDGEMENTS

I wish to acknowledge the following individuals whose enormous contributions led to the successful completion of this thesis:

- Dr. Dimitrios Goulias, thank you for giving me the opportunity to pursue this research study under your instruction and advice. I appreciate your tremendous patience during my challenging moments and motivation when I had doubts in myself. I am very honored to have been associated with you.
- Dr. Charles W. Schwartz, thank for your excellent inputs and suggestions throughout this research project.
- Dr. Aggour, Dr Aydilek, Dr. Cui and Dr. Lee thank you for taking time off your busy schedules to be on my committee.
- My parents, Habib and Fariba, you have always pushed me to be a better person and live a more meaningful life. I owe you a great debt of graduate. I love you both. Thank you.
- My sister, Nazli, you have been there for me during all the ups and downs. I can't thank you enough. I couldn't have completed this work without your push and support. I love you.

Table of Contents

Chapter 1: Research Overview

1.1 Introduction

State transportation agencies are responsible for assuring that materials produced, supplied, and placed on construction projects meet quality requirements set within material and construction specifications. Over the past two decades, the role of most of these agencies has shifted from monitoring the quality control of materials and placement techniques to quality assurance and acceptance. As a result, the contractor bears more responsibility for quality control during the production process. On the other hand, agency's role has been focusing on assurance of material quality and limited oversight of contractor quality control operations. Such shift in responsibilities is attributed to the modern transition from method and end-results specifications towards performance specs, and the adoption of Design-Build practice in construction. As a result, many agencies have begun to revise their materials acceptance specifications. In some cases, the revised specifications allow for the acceptance and payment of materials to be based on contractor, producer and/or supplier quality test results (Quality Control and certification testing) with complementary testing and inspection from agency to verify results (Quality Assurance). In other situations, QA data are used for acceptance and rewards based on quality at time of delivery. In addition, many specifications have been revised to assess material quality on statistical basis (Percent Within Limit) rather than individual or average test results. This allows for better incorporation of material variability in the acceptance and payment decision.

In the case of pavement construction, many state highway agencies have used pavement performance indicators as the basis of Hot-Mix Asphalt (HMA) construction specifications. Traditionally, volumetric properties of HMA such as Asphalt Content, air void content, Volume in the Mineral Aggregate, VMA, Voids Filled with Asphalt, VFA, density at the design number of gyrations, and aggregate gradation are the determining factors of predicted performance. Currently, the quality of HMA is primarily defined by the difference between the as-built mixture and the required specifications of the job mix formula (JMF), in terms of individual material parameters which are then used in identifying rewards or penalties for contractors. The less practiced warranty specification may also be used which identities withholding portion of the contract reward until the product performs well for a certain period of time. In recent years, the paving industry has been tempted to shift towards defining the quality of the pavement in terms of its performance. In such specification method, the contractor gets paid on the basis of the difference in predicted service life between the as-designed and the as-built pavement. In addition, in such a specification, it is described how the finished pavement must perform over time. Therefore, in order to be able to pay the contractor based on predicted performance, multiple studies have linked the volumetric properties of HMA to its performance (i.e., the service life).

On the other hand, state agencies have also been concerned about the risk associated with their sampling procedure specified for each pavement job. In addition, the American Association of State Highway and Transportation Officials (AASHTO) has suggested certain levels of risks for the contractor and agency, (i.e., Type I and II risks) depending on the nature and criticality of the construction facility and potential implications in terms of fatalities and/or economic impact.

The overall objective of this study was to develop a universal methodology for evaluating Type I and Type II acceptance risks, and relate these to economic consequences, and thus pay factors using performance models. The suggested methodology can be applied to any construction material specifications and will allow to balance pay factors with the associated statistical acceptance risks. To illustrate the various stages of the suggested methodology the case study of Hot-Mix Asphalt (HMA) was used.

1.2 Research approach

The various steps undertaken for defining the proposed methodology included:

1- *Review of current material QA/QC procedures*

In order to better understand the current QA practice of the material under study, it is critical to study the associated literature on QA/QC procedures. This study focuses on HMA. Thus, the current state of the art in HMA specifications from various states, the guidelines of FHWA for designing HMAs, recent national studies on specifications, performance models and recommended pay factor equations were reviewed.

2- Identification of key factors

Examining the accepted QA/QC procedures allows to identify the key factors that affect the quality of the material and ultimately its performance. Most construction materials have a long list of factors that affect the final product. Therefore, the focus should be on the prominent variables which affect the quality and performance and have been thoroughly examined and documented over the years.

3- Correlation among key factors

The correlation among the key material quality and performance parameters should be examined since it will affect the acceptance risks for both the agency and producer. From the HMA literature review several studies concluded that the effect of correlation among key factors on the final pay factors and risk levels are minimal and often ignored during the specification development. Such results of the aforementioned studies are discussed in detail in the literature review section.

4- Statistical distributions

In cases where significant historical data on the identified key parameters are available, the best fitting distribution to the data should be utilized for the analysis. The distribution will be the main input for the simulation of lots and sublots which will be utilized for quantifying risks. As encountered in many construction processes and documented by various studies the assumption of a normal distribution holds in the majority of construction materials production. For non-normally distributed cases simulation and quantification of acceptance risks is still possible.

5- Operational Characteristic (OC) Curves

In general, OC curves are a very common tool in estimating Type I and Type II risks. The OC curves allow for determining the contractor and agency risks of individual key factors corresponding to the material and/or construction specs currently used. The steps necessary to build the OC curves involves use of standard error of the population in order to relate percent within limit (PWL) and probability of acceptance (PoA). This process is extensively described in the study by Villiers, et al. 2003. The OC curves are utilized in calculating the risks associated to each material parameter that plays an important role in the quality of the end product, in this case HMA. OC curves have been recently used in relating PWL to PF and risks (Zhao and Goulias 2021a, 2021b, 2022) for multiple acceptance criteria in pavement structures.

6- Statistical parameters for defining acceptance risk

Both contractor and agency risks are estimated based on production samples. Furthermore, agencies use product quality measures for defining material specifications. Such measures include:

a. Tolerance limits: the maximum and minimum acceptable value of each measured parameter.
b. Rejectable Quality Level (RQL): The minimum level of quality that the material is unacceptable and rejected.
c. Acceptable Quality Level (AQL): The maximum level of quality that the material is fully acceptable at 100% pay.

d. Sample size: The number of samples taken from a production unit (usually lots) in order to make acceptance decisions.

7- Balancing risks and pay factors

The pay factor functions usually consider the performance of the as-built product versus the design quality. In order to balance pay factors and risk levels, it is necessary to perform Monte Carlo simulations in order to assess the impact of the key material quality parameters on risks and the pertinent rewards. Such simulations allow the decision makers to understand the effect of each material property and specification parameter on the overall risk levels and the pay factors which will play an important role in deciding the necessary adjustments to acceptance criteria and the specifications.

1.3 Organization of the Dissertation

The first Chapter of the study presents the introduction, research objectives, the analysis approach, and the organization of the dissertation. Chapter 2 presents a brief review of HMA requirements and material properties, and a review on the quality indicators and terms for defining acceptance risks. Chapter 3 includes the initial exploratory analysis and key components on calculating risks and pay factors for HMAs, which lays the ground for further in-depth development of the proposed methodology undertaken in the following chapters. Chapter 4 presents the analysis used in this research for simulating alternative scenarios which will lead to the suggested methodology for balancing risk levels with pay factors. Finally, Chapter 5 presents the proposed methodology to achieve the overall goal of balancing risks and pay factors, and applying the suggested methodology to the case of HMA.

***** THIS PAGE IS INTENTIONALLY LEFT BLANK *****

Chapter 2: Literature Review

Objective of this review was to assess the existing approach used by various agencies and contractors to assure the quality of materials used on construction projects. Furthermore, the review focused on HMA's quality indicators and performance measures and the state of quality assurance, risk levels and pay factors.

2.1 HMA Durability and Performance

Among other properties, the design of HMA mixtures requires balancing properties related to permanent deformation resistance (i.e., rutting), fatigue cracking, durability, strength and modulus. The ultimate goal is to maximize pavement service life within the provided project constraints and budget. Durability can be significantly affected by several material and mixture parameters, including asphalt binder type and content (AC), air voids and other mix volumetric properties. In addition to increasing the effective asphalt binder content, other parameters are looked at for improving durability, including:

- Changes to the design air voids
- Increasing minimum voids in mineral aggregate requirements
- Imposing a maximum voids in mineral aggregate skeleton
- Increasing the voids filled with asphalt
- Lower design compaction levels
- Increasing required field compaction levels

Many of these factors are interrelated, therefore, their modification must be considered with care to avoid unintended consequences in regard to resistance to permanent deformation, fatigue cracking, and other structural distresses (Karimi, 2009).

The NCHRP 704 national study on “A Performance-Related Specification for Hot-Mixed Asphalt” suggested important elements of a performance-related specification (PRS) for hot-mix asphalt (HMA). The NCHRP 704 study introduces the dynamic modulus, E*, as a fundamental material property of the AC layer. The dynamic modulus equation that has been adopted in this work is shown in Equation 2.1, identified as the Witczak Predictive Equation (WPE). WPE was developed on data based on many projects around the US and is relating E* to key material and mixture quality related parameters, such as volumetric properties, aggregate gradation, and binder viscosity (stiffness) of the AC layer. These are also the main properties that often are considered in QA specifications for AC construction.

Equitation 2.1 Dynamic modulus equation - Witczak Predictive Equation (WPE), (NCHRP 704)

$$Log\ E^* = -1.249937 + 0.029232\ p_{200} - 0.001767\ (p_{200})^2 - 0.002841\ p_4 - 0.058097\ V_a - 0.8022\ \frac{V_{beff}}{(V_{beff}+V_a)} + \frac{3.87197 - 0.0021\ p_4 + 0.003958\ p_{38} - 0.000017\ (p_{38})^2 + 0.00547\ p_{34}}{1+e^{(-0.603313-0.31335\ \log(f)-0.393532\ \log(\eta))}} \quad (1)$$

where

E^* = Asphalt Mix Dynamic Modulus, in 10^5 psi
η = bitumen viscosity in 10^6 poise
f = loading frequency in Hz
V_a = air voids in the mix, by volume, %
V_{beff} = effective bitumen content, by volume, %
p_{34} = cumulative % retained on the ¾ inch sieve
p_{38} = cumulative % retained on the ⅜-inch sieve
p_4 = cumulative % retained on the No. 4 sieve
p_{200} = % passing the No. 200 sieve

2.2 Acceptance Plans

Acceptance plans are defined by the "*Glossary of Highway Quality Assurance Terms*" (The Transportation Research Circular E-C074, 2005) as "an agreed-upon procedure for taking samples and making measurements or observations on these samples for the purpose of evaluating the acceptability of a lot of material or construction." Furthermore, it is critical to have a robust sampling plan in order to avoid having a biased specification. The "Statistical Acceptance Plan for Asphalt Pavement Construction. U.S. Army Corps of Engineers," by Freeman and Grogan (1998) define alternative specification categories. Suggested specification types and sampling plans are well summarized in the "Methodology To Develop A Minimum Cost Acceptance Sampling Plan For Highway Construction" study by Wazalwar (2009) and are listed below:

Single specification limit, single decision criterion: used when a material must be controlled above a minimum or below a maximum. Therefore, a single Acceptable Quality Level, AQL, (i.e., minimum level of quality that the material is 100% acceptable) is set and a binary decision on whether the material is accepted or rejected is made.

Single specification limit, dual decision criteria: An AQL and Rejectable Quality Level, RQL, (i.e., the maximum level of quality that the material is fully unacceptable) are set. Material at or above AQL is accepted at full or bonus pay, while material below RQL is rejected with no pay. Material with quality levels between AQL and RQL is usually accepted at a reduced pay according to a pre-determined pay factor.

Dual specification limits, single decision criterion: Dual specification limits are used when a material must be controlled within a range of values. The percent of material between these values is calculated as the Percent within Limit (PWL). Material is then either accepted or rejected and there is no pay factor provision.

Dual specification limits, dual decision criteria: AQL and RQL are set. Material at or above AQL is accepted at full or bonus pay while material below RQL is rejected with no pay. Material with an estimated quality level between AQL and RQL is usually accepted at reduced pay according to a pay scale.

2.3 Quality Indicators

In "Increasing Durability of Hot Mix Asphalt Pavements Designed with The Superpave System", Karimi (2009), has laid out how several studies which have examined the use of alternative quality indicators for HMA mixtures. Burati and Weed (2006) investigated the accuracy and precision of typical quality measures (PWL, AAD and CI, defined next). From the statistical point of view an accurate quality measure is a measure that provides an unbiased estimate for the corresponding population parameter. A precise estimator is an estimator with low variability. The suggested quality measures are summarized below:

1- Percent Within Limits (PWL)

In order to estimate the percent within limit (PWL) the Q-value is used with a PWL table (Table 2.1).

Equitation 2.2 Quality Index for the lower spec limit

$$QL = (X-LSL)/s$$

Equitation 2.3 Quality Index for the upper spec limit

$$QU= (USL-X)/s$$

Where:

QL = quality index for the lower spec limit

QU= quality index for the upper spec limit

X= sample mean for the lot

s= sample standard deviation for the lot

LSL= lower spec limit

USL=upper spec limit

Then using a PWL table, the total PWL is estimated (PWLT = PWLU + PWLL – 100).

Where:

PWLu =percent below the upper specification limit (based on Qu)

PWLL=percent above the lower specification limit (based on QL)

PWLT=percent within the upper and lower specification limits

As seen in the equations above, this process takes both the mean and standard deviation into account. Figure 2.1 illustrates some of these parameters and the Percent Defective material, PD= 100-PWL.

Table 2.1 Quality Index values for estimating PWL (Burati et al, 2003)

PWL	*n* = 3	*n* = 4	*n* = 5	*n* = 6	*n* = 7	*n* = 8	*n* = 9	*n* = 10 to 11
100	1.16	1.50	1.79	2.03	2.23	2.39	2.53	2.65
99	–	1.47	1.67	1.80	1.89	1.95	2.00	2.04
98	1.15	1.44	1.60	1.70	1.76	1.81	1.84	1.86
97	–	1.41	1.54	1.62	1.67	1.70	1.72	1.74
96	1.14	1.38	1.49	1.55	1.59	1.61	1.63	1.65
95	–	1.35	1.44	1.49	1.52	1.54	1.55	1.56
94	1.13	1.32	1.39	1.43	1.46	1.47	1.48	1.49
93	–	1.29	1.35	1.38	1.40	1.41	1.42	1.43
92	1.12	1.26	1.31	1.33	1.35	1.36	1.36	1.37
91	1.11	1.23	1.27	1.29	1.30	1.30	1.31	1.31
90	1.10	1.20	1.23	1.24	1.25	1.25	1.26	1.26
89	1.09	1.17	1.19	1.20	1.20	1.21	1.21	1.21
88	1.07	1.14	1.15	1.16	1.16	1.16	1.16	1.17
87	1.06	1.11	1.12	1.12	1.12	1.12	1.12	1.12
86	1.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08
85	1.03	1.05	1.05	1.04	1.04	1.04	1.04	1.04
84	1.01	1.02	1.01	1.01	1.00	1.00	1.00	1.00
83	1.00	0.99	0.98	0.97	0.97	0.96	0.96	0.96
82	0.97	0.96	0.95	0.94	0.93	0.93	0.93	0.92
81	0.96	0.93	0.91	0.90	0. 90	0.89	0.89	0.89
80	0.93	0.90	0.88	0.87	0.86	0.86	0.86	0.85
79	0.91	0.87	0.85	0.84	0.83	0.82	0.82	0.82
78	0.89	0.84	0.82	0.80	0.80	0.79	0.79	0.79
77	0.87	0.81	0.78	0.77	0.76	0.76	0.76	0.75
76	0.84	0.78	0.75	0.74	0.73	0.73	0.72	0.72
75	0.82	0.75	0.72	0.71	0.70	0.70	0.69	0.69
74	0.79	0.72	0.69	0.68	0.67	0.66	0.66	0.66
73	0.76	0.69	0.66	0.65	0.64	0.63	0.63	0.63
72	0.74	0.66	0.63	0.62	0.61	0.60	0.60	0.60
71	0.71	0.63	0.60	0.59	0.58	0.57	0.57	0.57
70	0.68	0.60	0.57	0.56	0.55	0.55	0.54	0.54
69	0.65	0.57	0.54	0.53	0.52	0.52	0.51	0.51
68	0.62	0.54	0.51	0.50	0.49	0.49	0.48	0.48
67	0.59	0.51	0.47	0.47	0.46	0.46	0.46	0.45
66	0.56	0.48	0.45	0.44	0.44	0.43	0.43	0.43
65	0.52	0.45	0.43	0.41	0.41	0.40	0.40	0.40
64	0.49	0.42	0.40	0.39	0.38	0.38	0.37	0.37
63	0.46	0.39	0.37	0.36	0.35	0.35	0.35	0.34
62	0.43	0.36	0.34	0.33	0.32	0.32	0.32	0.32
61	0.39	0.33	0.31	0.30	0.30	0.29	0.29	0.29
60	0.36	0.30	0.28	0.27	0.27	0.27	0.26	0.26
59	0.32	0.27	0.25	0.25	0.24	0.24	0.24	0.24
58	0.29	0.24	0.23	0.22	0.21	0.21	0.21	0.21
57	0.25	0.21	0.20	0.19	0.19	0.19	0.18	0.18
56	0.22	0.18	0.17	0.16	0.16	0.16	0.16	0.16
55	0.18	0.15	0.14	0.14	0.13	0.13	0.13	0.13
54	0.14	0.12	0.11	0.11	0.11	0.11	0.10	0.10
53	0.11	0.09	0.08	0.08	0.08	0.08	0.08	0.08
52	0.07	0.06	0.06	0.05	0.05	0.05	0.05	0.05
51	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03
50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Specification Conformity Analysis, *FHWA Technical Advisory T5080.12*, June 23, 1989

Table 2.1 Quality Index values for estimating PWL continued (Burati et al, 2003)

PWL	$n = 12$ to 14	$n = 15$ to 18	$n = 19$ to 25	$n = 26$ to 37	$n = 38$ to 69	$n = 70$ to 200	$n = 201$ to ∞
100	2.83	3.03	3.20	3.38	3.54	3.70	3.83
99	2.09	2.14	2.18	2.22	2.26	2.29	2.31
98	1.91	1.93	1.96	1.99	2.01	2.03	2.05
97	1.77	1.79	1.81	1.83	1.85	1.86	1.87
96	1.67	1.68	1.70	1.71	1.73	1.74	1.75
95	1.58	1.59	1.61	1.62	1.63	1.63	1.64
94	1.50	1.51	1.52	1.53	1.54	1.55	1.55
93	1.44	1.44	1.45	1.46	1.46	1.47	1.47
92	1.37	1.38	1.39	1.39	1.40	1.40	1.40
91	1.32	1.32	1.33	1.33	1.33	1.34	1.34
90	1.26	1.27	1.27	1.27	1.28	1.28	1.28
89	1.21	1.22	1.22	1.22	1.22	1.22	1.23
88	1.17	1.17	1.17	1.17	1.17	1.17	1.17
87	1.12	1.12	1.12	1.12	1.12	1.13	1.13
86	1.08	1.08	1.08	1.08	1.08	1.08	1.08
85	1.04	1.04	1.04	1.04	1.04	1.04	1.04
84	1.00	1.00	1.00	1.00	0.99	0.99	0.99
83	0.96	0.96	0.96	0.96	0.95	0.95	0.95
82	0.92	0.92	0.92	0.92	0.92	0.92	0.92
81	0.89	0.88	0.88	0.88	0.88	0.88	0.88
80	0.85	0.85	0.85	0.84	0.84	0.84	0.84
79	0.82	0.81	0.81	0.81	0.81	0.81	0.81
78	0.78	0.78	0.78	0.78	0.77	0.77	0.77
77	0.75	0.75	0.75	0.74	0.74	0.74	0.74
76	0.72	0.71	0.71	0.71	0.71	0.71	0.71
75	0.69	0.68	0.68	0.68	0.68	0.68	0.67
74	0.66	0.65	0.65	0.65	0.65	0.64	0.64
73	0.62	0.62	0.62	0.62	0.62	0.61	0.61
72	0.59	0.59	0.59	0.59	0.59	0.58	0.58
71	0.57	0.56	0.56	0.56	0.56	0.55	0.55
70	0.54	0.53	0.53	0.53	0.53	0.53	0.52
69	0.51	0.50	0.50	0.50	0.50	0.50	0.50
68	0.48	0.48	0.47	0.47	0.47	0.47	0.47
67	0.45	0.45	0.45	0.44	0.44	0.44	0.44
66	0.42	0.42	0.42	0.42	0.41	0.41	0.41
65	0.40	0.39	0.39	0.39	0.39	0.39	0.39
64	0.37	0.36	0.36	0.36	0.36	0.36	0.36
63	0.34	0.34	0.34	0.34	0.33	0.33	0.33
62	0.31	0.31	0.31	0.31	0.31	0.31	0.31
61	0.29	0.29	0.28	0.28	0.28	0.28	0.28
60	0.26	0.26	0.26	0.26	0.26	0.25	0.25
59	0.23	0.23	0.23	0.23	0.23	0.23	0.23
58	0.21	0.21	0.20	0.20	0.20	0.20	0.20
57	0.18	0.18	0.18	0.18	0.18	0.18	0.18
56	0.16	0.15	0.15	0.15	0.15	0.15	0.15
55	0.13	0.13	0.13	0.13	0.13	0.13	0.13
54	0.10	0.10	0.10	0.10	0.10	0.10	0.10
53	0.08	0.08	0.08	0.08	0.08	0.08	0.08
52	0.05	0.05	0.05	0.05	0.05	0.05	0.05
51	0.03	0.03	0.03	0.03	0.03	0.03	0.02
50	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Specification Conformity Analysis, *FHWA Technical Advisory T5080.12*, June 23, 1989

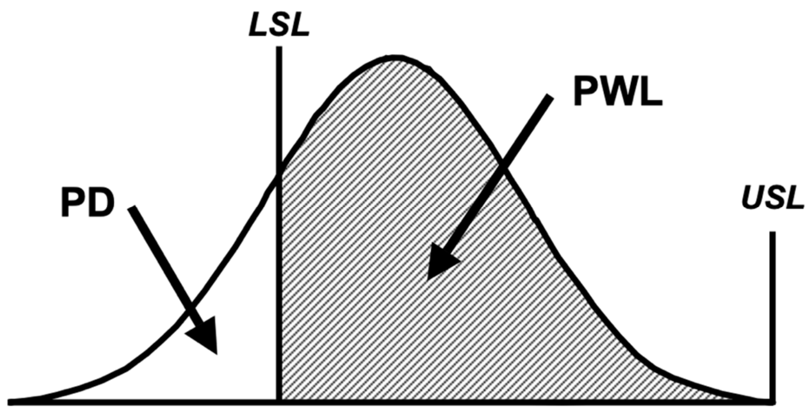


Figure 2.1 Relationship between PWL (= 100- PD), USL and LSL (Burati et al, 2003)

2- The Average Absolute Deviation (AAD) Quality Measure

The average absolute deviation from the target is calculated using the following equation

Equitation 2.4 Average Absolute Deviation Equation

$AAD = (\sum |Xi-T|)/n$

Where:

Xi = individual test results

T = target value

n = number of tests per lot

3- Conformal Index (CI)

The concept of CI is very similar to AAD. The AAD uses the average of the absolute values of the deviations from the target value, but CI uses the squares of the deviations from the target values. Both CI and AAD do not allow the contractor to adjust the process at the middle of a lot production. This occurs by not allowing the negative and positive deviations to cancel out.

Equitation 2.5 Conformal Index Equation

$CI=\sqrt{\sum(X_i-T)^2/n}$

Where:

X_i = individual test results

T = target value

n = number of tests per lot

2.3 Components of Acceptance Plans & Definitions of Risks

There are generally two types of acceptance plans: 1) The accept/reject acceptance plans; and, 2) the acceptance plans that include pay adjustment provisions (Burati et. al., 2003). These methods are presented next using specific studies from the literature.

As summarized by Wazalwar (2009) and Villiers et al. (2003), the components of any acceptance sampling plan are briefly described below.

Lot: This is the amount of construction or material that may be accepted with pay and/or pay adjustment or rejected based on the "as-constructed" quality characteristic. A lot represents the amount of material or constructed product (e.g., pavement) produced by essentially the same process, so that the probability distributions of AQCs are likely to be uniform and as in many construction events may follow the normal distribution. A reasonable way to define a lot is a one-day production, a batch production, other.

Sample size: The sample size refers to the number of tests or measurements for each AQC taken randomly from the lot. Randomness of sampling is a vital assumption upon which the statistical acceptance procedure is based. Random sampling can be defined as a manner of sampling that allows every part of the production population (i.e., lot) to have an equal opportunity of appearing in the sample.

Acceptable Quality Level (AQL): The minimum level of quality that the material is fully acceptable

Rejectable Quality Level (RQL): The maximum level of quality that the material is fully unacceptable

Risks Involved in Acceptance: The risks involved in acceptance procedure are calculated on the basis of the hypothesis:

a) Buyer's risk (β): The probability that the buyer would accept poor quality material. Often also identified as Type I risk.
b) Seller's risk (α): The probability that seller's good quality material would be rejected. Often also identified as Type II risk

The AQL and RQL are the parameters that agencies can utilize to determine incentives and penalties. Each state sets its own AQL and RQL and for several states these values are set at 90% and 40% respectively. Florida DOT is using 90% and 50% for these values respectively. Using OC curves, Villiers et al. (2003) illustrated that with the current Florida DOT's specification limits (AQL = 90% and RQL = 50%) produce buyer's risks equal to 33 and 24% respectively for sampling sizes of 4 or 5 per lot (Figure 2.1). In order to achieve the AASHTO recommended risk level of 5% (Table

2.3) ten samples per lot were required. Since this number of sampling is not economically feasible in terms of QC cost, it was required to adjust AQL and RQL in order to achieve the 1% and 5% seller and buyer's risk. After constructing the OC curves and setting the risks at the suggested levels, it was concluded that the agency needs to change their AQL and RQL. Table 2.2 summarizes these values.

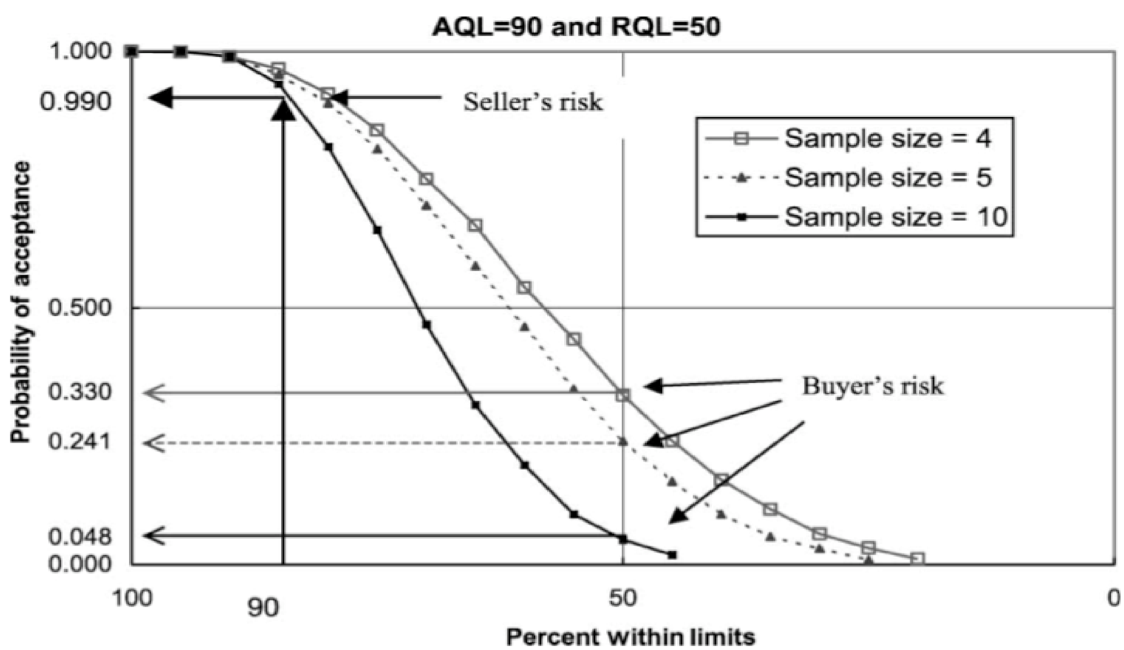


Figure 2.2 Contactor and Owner Risk using Unknown Standard Deviation (Villiers et al. 2003)

Table 2.2 Calculated AQL and RQL Based on Different Sample Sizes (Villiers et al. 2003)

Sample Size	AQL	RQL
3	91	17
4	87	20
5	85	23
6	83	25
10	71	28

Therefore, the agency needed to either increase sampling size or adjust the AQL and RQL values to achieve the recommended risk levels.

AASHTO R9-97 serves as the main reference point for suitable risk levels of acceptance plans. These risk level suggestions are based on the criticality of the measured property as it affects safety, performance, durability, and/or cost implications as shown in Table 2.3.

Table 2.3 Recommended risk levels by AASHTO R-9

Criticality[1]	Recommended α	Recommended β
Critical	0.050	0.005
Major	0.010	0.050
Minor	0.005	0.100
Contractual	0.001	0.200

[1]Critical: when the requirement is essential to preservation of life.
Major: when the requirement is necessary for the prevention of substantial financial loss.
Minor: when the requirement does not materially affect performance.
Contractual: when the requirement is established only to provide uniform standards for bidding.

Later version of AASHTO guidelines (AASHTO, 2005) do not provide specific recommendations for acceptable risks, but it states "the more critical the application, the lower should be the buyer's risk. But only under rare circumstances should the buyer's risk be lower than the seller's risk."

The study "State Construction Quality Assurance Programs" (NCHRP 346, 2005) describes the quality assurance practices of different state departments of transportation as it relates to highway materials and construction. The study provides a scale of the magnitude of the differences that are found in such programs and lists the following items agencies must consider:

- Choosing the attributes and test methods to use for QC and for acceptance
- Deciding on the point of sampling to use for QC and for acceptance.
- Deciding who establishes the frequency for QC tests.
- Deciding how to establish the QC tests.
- Deciding on the quality measure to use for acceptance.
- Deciding whether accept/reject or pay adjustment provisions will be used.
- Deciding what levels of risks are appropriate for the agency and contractor.
- Deciding whether contractor tests will be used in the acceptance decision:
    - if they are, deciding on the type of verification system that will be used;
    - whether the agency will use split samples, independent samples, or both; and
    - the purpose of the verification.
- Deciding if training and/or certification will be required, and, if required, determining who will perform it.
- Deciding how the independent assurance, IA, function will be administered.

NCHRP 346 further describes the quality assurance programs for soils and embarkments, aggregate base and subbase, and hot-mix asphalt (HMA). For HMA, the study notes that, QA programs used to control and accept HMA tend to be different from other materials. As Figure 2.3 illustrates, 21 agencies use QA programs with the contractor controlling quality and agency performing acceptance, and 25 agencies use

QA programs with the contractor controlling the quality and the agency using contractor test results in the acceptance decision.

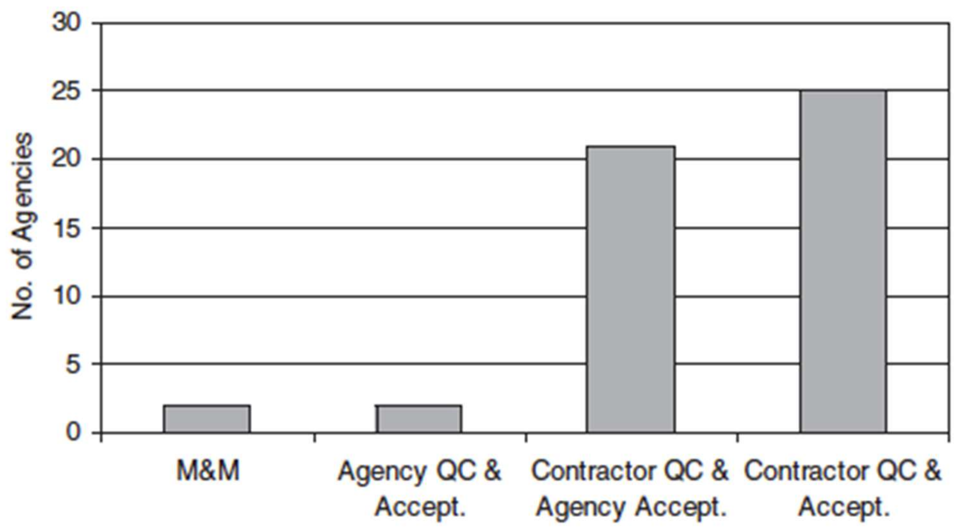


Figure 2.3 QA program types for HMA across 45 different agencies (NCHRP 346)

As an example of such state agencies, Washington State Department of Transportation (WSDOT) performed a study titled "Material Risk Analysis" (Baker et al, 2010). The study describes materials risk analysis process undertaken by WSDOT. The study used the Delphi process to rate the risk of having a material fail to meet specification and the consequences of that material failing to meet specification based on experts' opinion. Results were categorized into four categories for either more or less intensive examination by the state highway authority: "highest risk materials undergo physical acceptance testing or are inspected during fabrication under a manufacturer's quality system plan; moderate risk materials are accepted through the manufacturer's certification of compliance; lower risk materials are accepted with a manufacturer's certification or with a catalog cut; and the lowest risk materials are accepted through visual inspection in the field." Figure 2.4 below depicts this acceptance rating matrix.

FIGURE A, Acceptance Rating Matrix

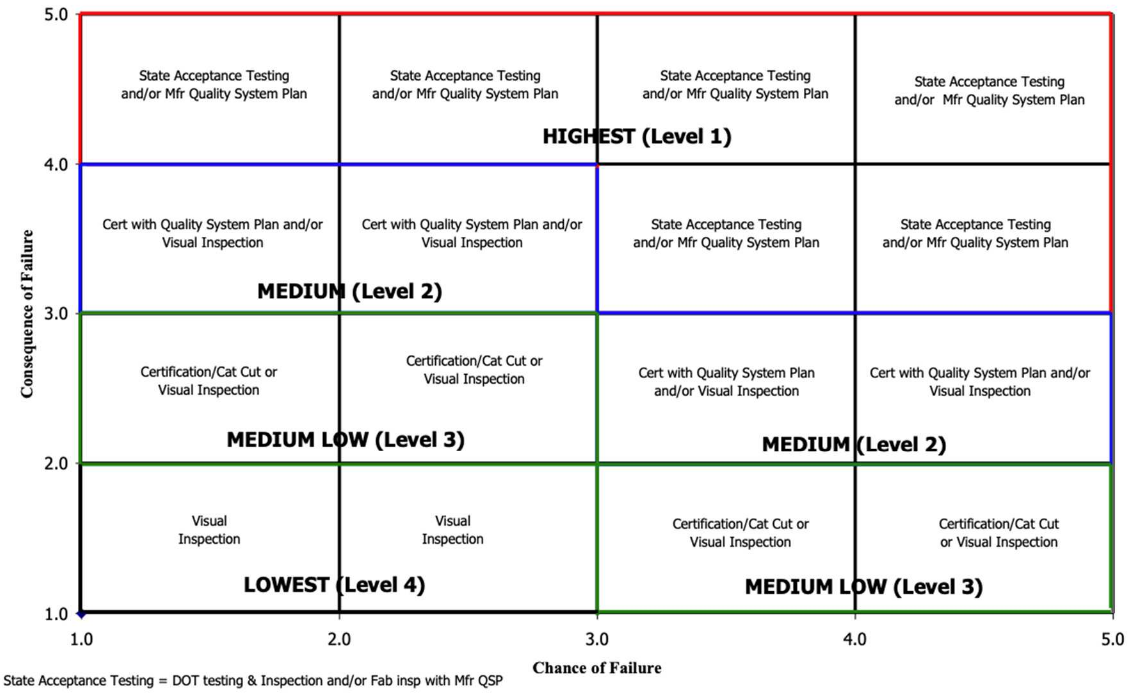


Figure 2.4 Materials Acceptance Rating Matrix, depicting different levels of risk and different acceptance criteria ((Baker et al, 2010)

2.4 Pay Factors

As identified by the "Optimal Procedures for Quality Assurance Specifications" (Burati et. al., 2003) study the early pay factors were designed as stepped schedules, such as that shown in Table 2.4 and Figure 2.3.

Table 2.4 Example Stepped Pay Factor based on PWL (Burati et. al., 2003)

Estimated PWL	Payment Factor, %
95.0 — 100.0	102
85.0 — 94.9	100
50.0 — 84.9	90
0.0 — 49.9	70

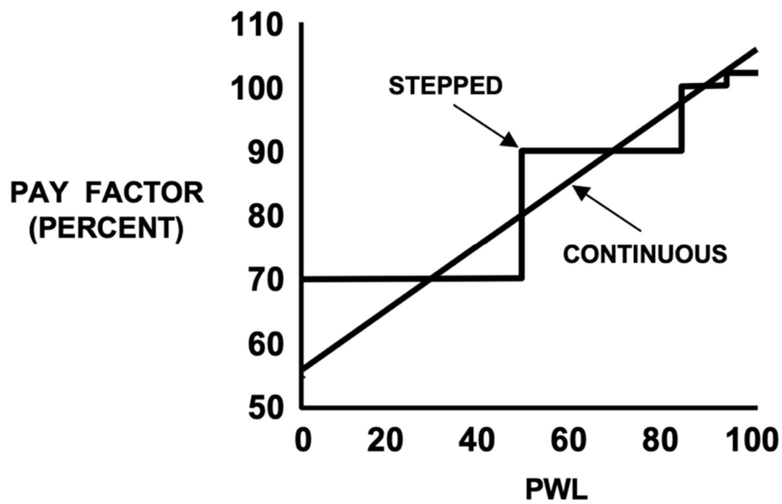


Figure 2.3 Example of stepped and Continuous Pay Factors (Burati et. al., 2003)

More recently, there has been a tendency to use continuous (i.e., function) pay factor such as that shown in equation 2.5 and previously used by Karimi (2009):

Equitation 2.5 Example of Continuous Pay Factor (Burati et. al., 2003)

PF = 55 + 0.5 PWL

Where:

PF = payment factor as a percent of contract price.

PWL = estimated percent within limits.

As it was concluded at the "Optimal Procedures for Quality Assurance Specifications" study, the continuous pay factor is advantageous since as opposed to the stepped function, two samples with minor differences will not end up with significantly different pays only due to chance.

The NCHRP 704 study estimates the pay factor penalty/bonus based on the predicted life difference (PDL) of each lot and notes that the criterion relating the PLD and the

Pay Factor (PF) for each distress is solely defined by the user agency. The Pay Factor (PF) is based on the loss or gain in the service life. Figure 2.4 shows the relationship between the PF and PLD.

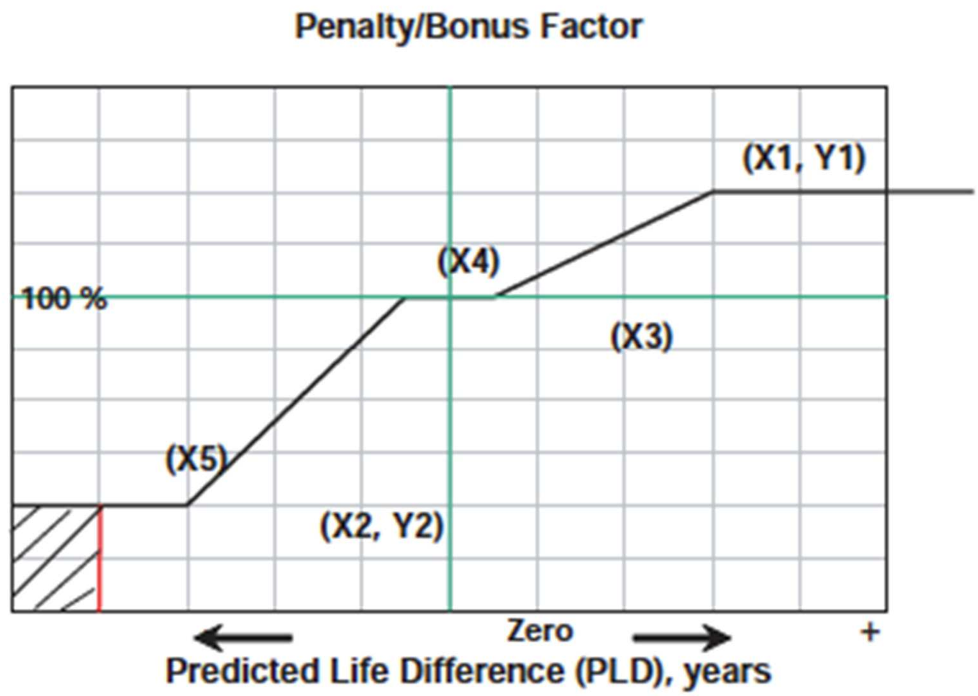


Figure 2.4 Penalty/Bonus versus pavement life difference relationship (NCHRP 704)

The NCHRP 704 study further notes that one of the first step for an agency is determination of maximum and minimum PF values. As the next step, relationships between PLD and pay adjustment factors can be developed. The PLD value calculated from each lot is then used to calculate the PF for the lot. The lot PF for each distress is then summed up to calculate the total PF for that distress (i.e., permanent deformation, cracking, other). The PF-PLD relationship can be tailored by the agency (or between the agency and contractor) on the basis of experience and policy. Adjustments to PF by indices such as the International Roughness Index (IRI) are also discussed in NCHRP 704. IRI is a standard measure of pavement smoothness and the inclusion of IRI into the pay factor may be considered by state agencies. Figure 2.5 below illustrates an example pay factor that considers IRI.

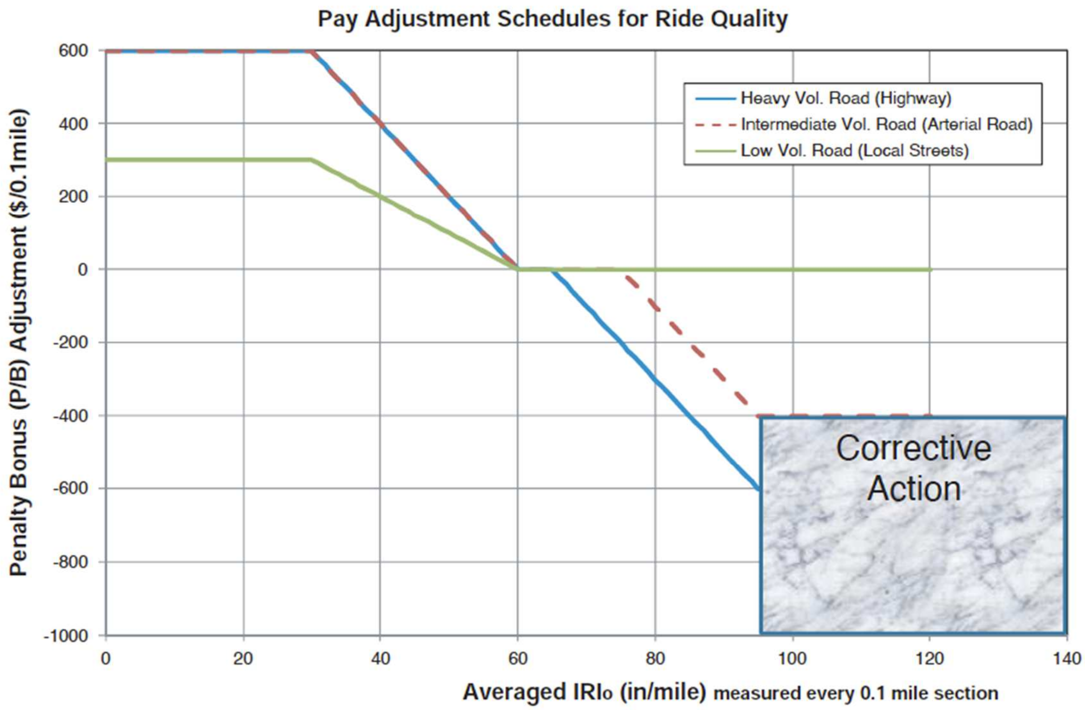


Figure 2.5 Penalty/Bonus versus pavement life difference relationship for IRI (NCHRP 704)

2.5 Development of Procedures and Guidelines

Ultimately, the goal is to develop procedure and guidelines that state agencies incorporate for assessing how well the material and construction projects perform while considering the practical limitations of production. The report titled "Procedures and Guidelines for Validating Contractor Test Data" (NCHRP 946, 2020) summarizes the results of a project with the following objectives: "(1) recommending procedures for validating contractor test data for construction materials and (2) preparing related guidelines, in the form of a proposed standard practice, for their application." NCHRP

946 also included the proposed practice for validating contractor test data as illustrated in Figure 2.6 below.

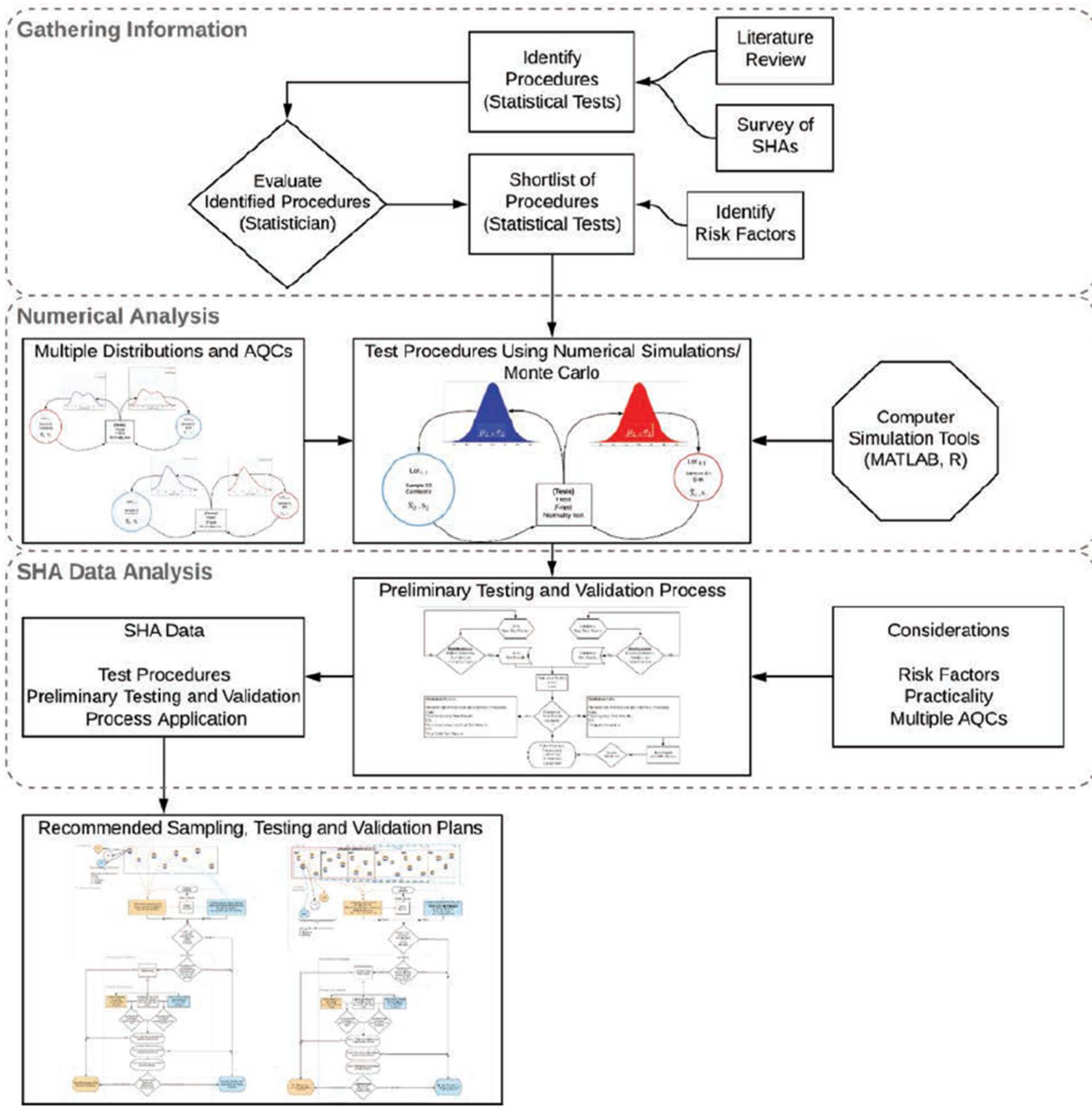


Figure 2.6 Three stages of developing a proposed practice for validating contractor test data (NCHRP 946)

NCHRP 946 also utilized a MATLAB code to scan and sort data based on the project number and lot number which were received from different state highway agencies.

The test results of a single lot were treated as a single sample. The summary of the analyzed data are summarized in Table 2.5 below.

Table 2.5 State highway agency data used for analysis (NCHRP 946)

SHA ID	Material Type	AQC	Number of Projects	Average Lots per Project	Total Samples (Lots)
SHA 1	HMA	Density	259	15	3,804
		AV	302	7	2,050
	PCC	Strength	16	22	354
		Thickness	16	22	354
SHA 2	PCC	Strength	18	1	25
SHA 3	HMA	Density	690	7	5,084
		AV	708	8	5,620
		AC	720	9	6,488
		No. 8 Sieve	720	9	6,487
		No. 200 Sieve	720	9	6,490
SHA 4	Aggregates Base	2 inch Sieve	3	41	123
		1 inch Sieve	3	41	123
		3/8 inch Sieve	3	41	123
		No. 10 Sieve	3	41	123
		No. 40 Sieve	3	41	123
		No. 200 Sieve	3	41	123
		Liquid Limit (LL)	3	41	123
		Plasticity Index (PI)	3	41	123
		Moisture Content (MC)	3	41	123
SHA 5	HMA	AV	289	6	1,734
		AC	289	6	1,734
		VMA	289	6	1,734

*** THIS PAGE IS INTENTIONALLY LEFT BLANK ***

Chapter 3: Initial Exploratory Analysis on Risks and Pay Factor

3.1 Introduction

In this stage, the research focused on HMA and how best to achieve the goal of developing a methodology that will allow for evaluating the following two risks and their relationship to pay factors (PF).

1- The acceptance risks associated with individual material parameters constituting the Dynamic Modulus (E*) when they are included in a specification.

2- The acceptance risks associated with E* itself as a single parameter of quality and performance criteria.

As discussed in chapter 2, the Dynamic Modulus (E*) currently represents a material quality parameter that the highway industry considers as a good performance indicator. Thus, its use in acceptance criteria of HMA is desirable. In order to assess the abovementioned acceptance risks, it is important to identify how E* is dependent on material and testing parameters.

3.2 Dynamic Modulus (E*)

As discussed in Chapter 2, Equation 3.1 represents a well-accepted proposed equation for estimating E* after a National Cooperative Highway Research Program (NCHRP) study, NCHRP 704. Furthermore, a set of reasonable values for each parameter was presented in that study with data from various DOTs around the US. These values were used herein in assessing the sensitivity of E* to each parameter.

Equation 3.1 Dynamic Modulus Equation adopted by NCHRP 704

$$Log\ E^* = -1.249937 + 0.029232\,P_{200} - 0.001767\,(P_{200})^2 - 0.002841\,P_4 - 0.058097\,V_a - 0.8022\,\frac{V_{beff}}{(V_{beff} + V_a)} + \frac{3.87197 - 0.0021\,P_4 + 0.003958\,P_{38} - 0.00017\,(P_{38})^2 + 0.00547\,P_{34}}{1 + e^{(-0.603313 - 0.31335\log(f) - 0.393532\log(\eta))}}$$

where the parameters that are used to calculate E* are:

- E* = Asphalt Mix Dynamic Modulus, in 10^5 psi
- η = bitumen viscosity, in 10^6 poise
- f = Load frequency, in Hz
- V_a = Air voids in the mix, by volume %
- V_{beff} = Effective bitumen content, by volume %
- P_{34} = cumulative % retained on ¾ sieve
- P_{38} = cumulative % retained on 3/8 sieve
- P_4 = cumulative % retained on No.4 sieve
- P_{200} = % passing on No. 200 sieve

The first set of values reported in the literature were from one of the first research studies on the Dynamic Modulus (Witczak and Fonesca, 1996). These values are listed in Table 3.1 and corresponded to an E* value of 1.4967 x 105 psi.

Table 3.1 Values for parameters constituting E* (Witczak and Fonesca 1996)

Parameter	Value
η= Viscosity	$15*10^5$ psi
f = Load frequency	16 Hz
V_a = Air voids in the mix	5.2 %
V_{beff} = Effective bitumen content	12.5%
P_{34} = Retained on ¾ sieve	15.0%
P_{38} = Retained on 3/8 sieve	31.5%
P_4 = Retained on No.4 sieve	56.0%
P_{200} = Passing on No. 200 sieve	5.1%

The NCHRP 704 study (*A Performance-Related Specification for Hot-Mixed Asphalt*, *2011*) has provided extended data from E* studies around the US. Therefore, such values were used as input to the analysis of this study. These values are tabulated in Table 3.2 and are used to assess the sensitivity of the Dynamic Modulus (Equation 3.1) in relation to each parameter. The value of each parameter ranged from +10% (max value) to -10% (min value) of the typical value reported in the NCHRP 704. The range of values were considered to be reasonable (for example capped at 100% when the prescribed range was above 100%) and achievable values in HMA production (as suggested by reported values in NCHRP 704 and other literature).

Table 3.2 Typical values for parameters constituting E* (NCHRP 704)

Parameter	Units	Min Value (-10%)	Typical Value	Max Value (+10%)
η	10^5 psi	0.361	0.401	0.441
f	Hz	51.408	57.120	62.832
Va	% volume	6.780	7.533	8.287
Vbeff	% volume	4.596	5.107	5.618
P34	% retained	90.000	100.000	100.000
P38	% retained	80.224	89.138	98.051
P4	% retained	37.845	42.050	46.255
P200	% passing	4.733	5.258	5.784

Furthermore, in order to assess the sensitivity of E* to each constituting parameter, each individual input in Table 3.2, was increased/decreased by 5, 10 and 20% while all the other input values were kept constant. Table 3.3 shows these values and the impact in E* due to each increase and decrease.

Table 3.3 Percentage change in E* per change of certain percentages in each parameter

Parameter	-10%	+10%	-5%	+5%	-20%	+20%
η	2.90%	2.61%	1.41%	1.34%	6.18%	4.97%
f	2.31%	2.08%	1.12%	1.06%	4.91%	3.96%
V_a	-5.69%	-6.25%	-2.92%	-3.06%	-10.69%	-12.98%
V_{beff}	-4.93%	-4.54%	-2.41%	-2.32%	-10.29%	-8.75%
P_{34}	9.78%	0.00%	4.89%	0.00%	19.56%	0.00%
P_{38}	-39.59%	-44.42%	-20.40%	-21.61%	-74.34%	-93.67%
P_4	-4.50%	-4.50%	-2.25%	-2.25%	-9.01%	-9.01%
P_{200}	1.49%	1.25%	0.72%	0.66%	3.22%	2.26%

In order to better visualize the tabulated values in Table 3.3, Figures 3.1 through 3.3 illustrate the effect of change in each parameter on E*.

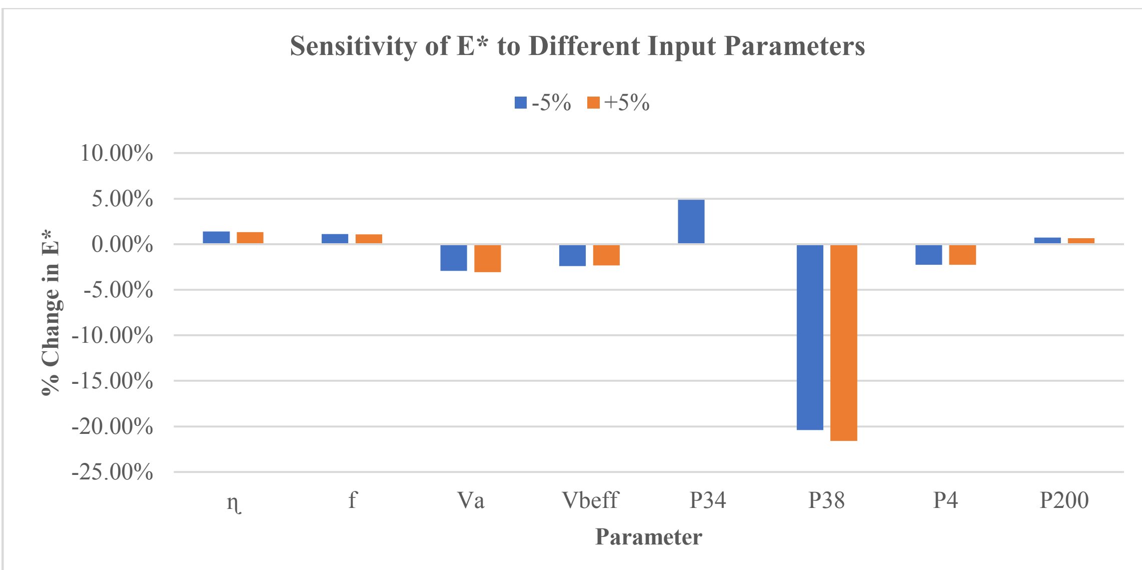


Figure 3.1 Sensitivity of E* to input parameters for ±5% change

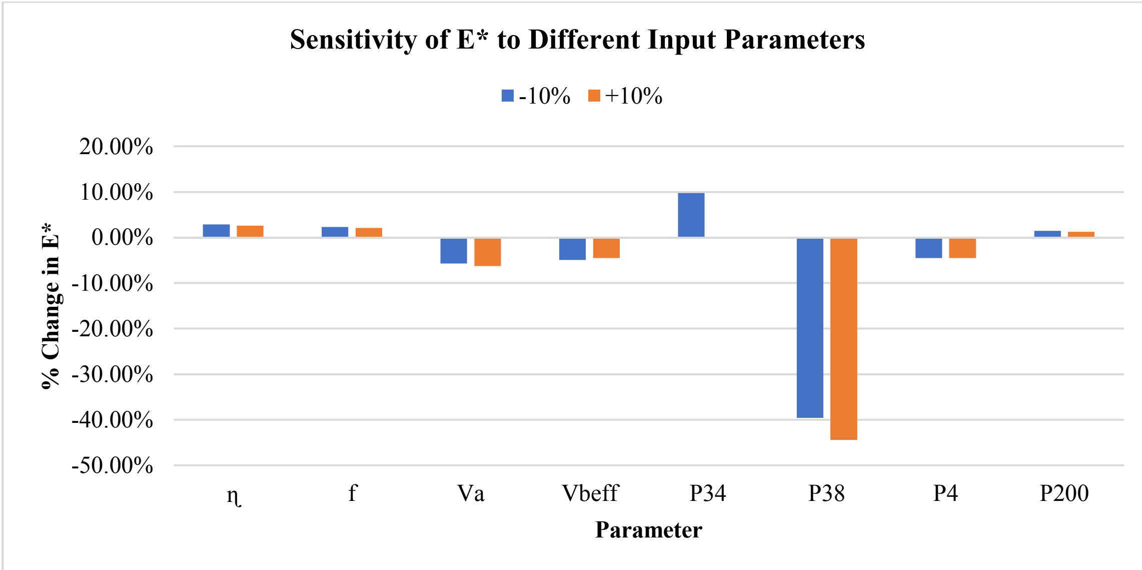


Figure 3.2 Sensitivity of E* to input parameters for ±10% change

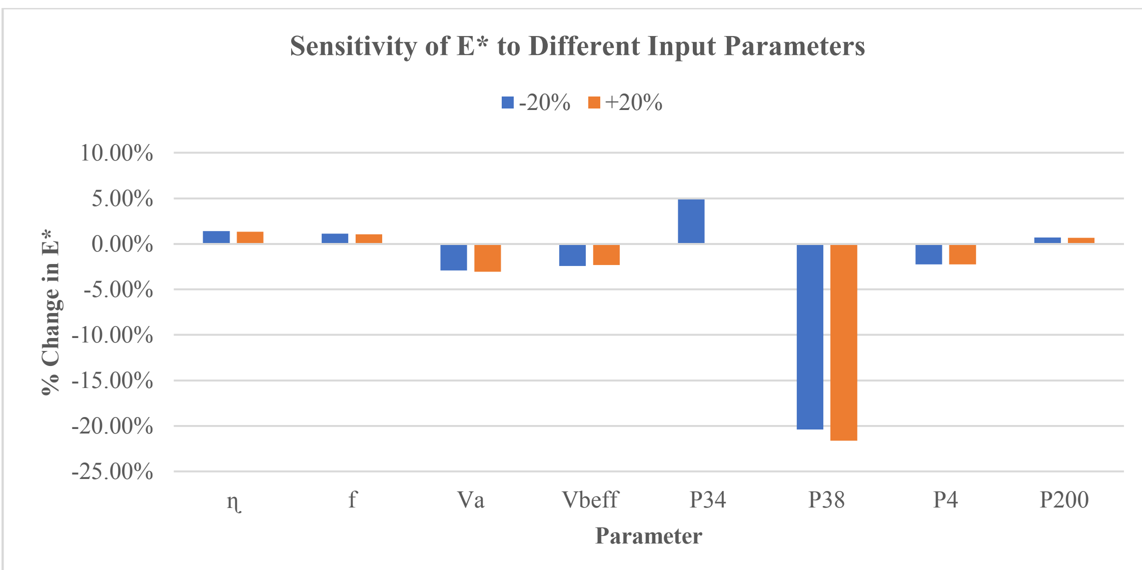


Figure 3.3 Sensitivity of E* to input parameters for ±20% change

As Figures 3.1 through 3.3 illustrate, the value of E* is most sensitive to P_{38} by a significant margin compared to other parameters. Therefore, when adjusting any aspect of the parameters (e.g., tolerances or production variability) in order to achieve a certain goal (such as balancing the risk levels and PF) most stress shall be placed on P_{38}.

3.3 Type I and II risks of Dynamic Modulus vs. pay factor

After determining the sensitivity of E* to each parameter, it is important to evaluate the Type I and Type II risks associated acceptance/rejection of product when E* serves as the deciding criteria. This determination is conducted using values of E* reported in the literature which assist with defining the population distribution (Table 3.4). The rational for defining the upper and lower specification limits (i.e., tolerances) is also described in Table 3.4. As discussed in Chapter 2, a commonly used tool in assessing Type I and Type II risks are the OC curves which are also utilized below. In summary, OC curves were used for assessing the Type I and Type II risks based on the values reported in Table 3.4

Table 3.4 Population distribution of E* distribution with upper and lower spec limits

Assumption	Reason/Source
Target E* = 374.057 ksi	NCHRP 704
Mean E* = 339.186 ksi	NCHRP 704 (average of all E* values)
Variance E* = 849 ➔ Std. Dev. = 30 ksi	NCHRP 704 considering variance of each reported lot based on $S_C^2 = \frac{\Sigma n_i S_i^2 + \Sigma n_i (\bar{x}_i - \bar{x}_c)^2}{\Sigma n_i}$
Upper and lower limits = ± 100 Therefore: LL= 274.1 ksi UL= No upper limit is set, since higher E* means higher Y (i.e., better quality).	Per NCHRP 704, the payment for the mentioned parameters in Table 3.2 is equal to 100%. Assuming that 100% pay occurs when 100% of each lot/sample is within limits and E* is normally distributed, ±3 times the standard deviation around the mean of E* will encompass ~100%. Therefore, the lower and upper limit can be set at 3 standard deviations above and below the mean E* value.

For building the OC curves and with regards to Type I and Type II errors, the following terms are used, as provided by the FHWA “Optimal Procedures for Quality Assurance Specifications” study (Burati et. al. 2003):

OC Curve: A graphic representation of an acceptance plan that shows the relationship between the actual quality of a lot and either (1) the probability of its acceptance (for accept/reject acceptance plans) or (2) the probability of its acceptance at various payment levels (for acceptance plans that include pay adjustment provisions)

Seller's risk (α): also called risk of a type I error. The probability that an acceptance plan will erroneously reject acceptable quality level (AQL) material or construction with respect to a single acceptance quality characteristic. It is the risk the contractor or producer takes in having AQL material or construction rejected.

Buyer's risk (β): also called risk of a type II error. The probability that an acceptance plan will erroneously fully accept (100 percent or greater) rejectable quality level (RQL) material or construction with respect to a single acceptance quality characteristic. It is the risk the highway agency takes in having RQL material or construction fully accepted.

In addition, the TRB glossary (Transportation Research Circular No. E-C037) offers the following definitions for AQL and RQL

AQL: That minimum level of actual quality at which the material or construction can be considered fully acceptable (for that quality characteristic). For example, when quality is based on PWL, the AQL is that actual (not estimated) PWL at which the quality characteristic can just be considered fully acceptable. Acceptance plans should be designed so that AQL material will receive an PF of 100%.

RQL: That maximum level of actual quality at which the material or construction can be considered unacceptable (rejectable). For example, when quality is based on PD, the RQL is that actual (not estimated) PD at which the quality characteristic can just be considered fully rejectable. It is desired to require removal and replacement, corrective action, or the assignment of a relatively low pay factor when RQL work is detected.

Therefore, based on the definitions, the seller's risk (α) and the buyer's risk (β) are calculated at AQL and RQL respectively.

Applying the methodology of building OC curves to the data reported in Table 3.4, the following curves were generated for sample sizes of 20, 8, 5 and 2.

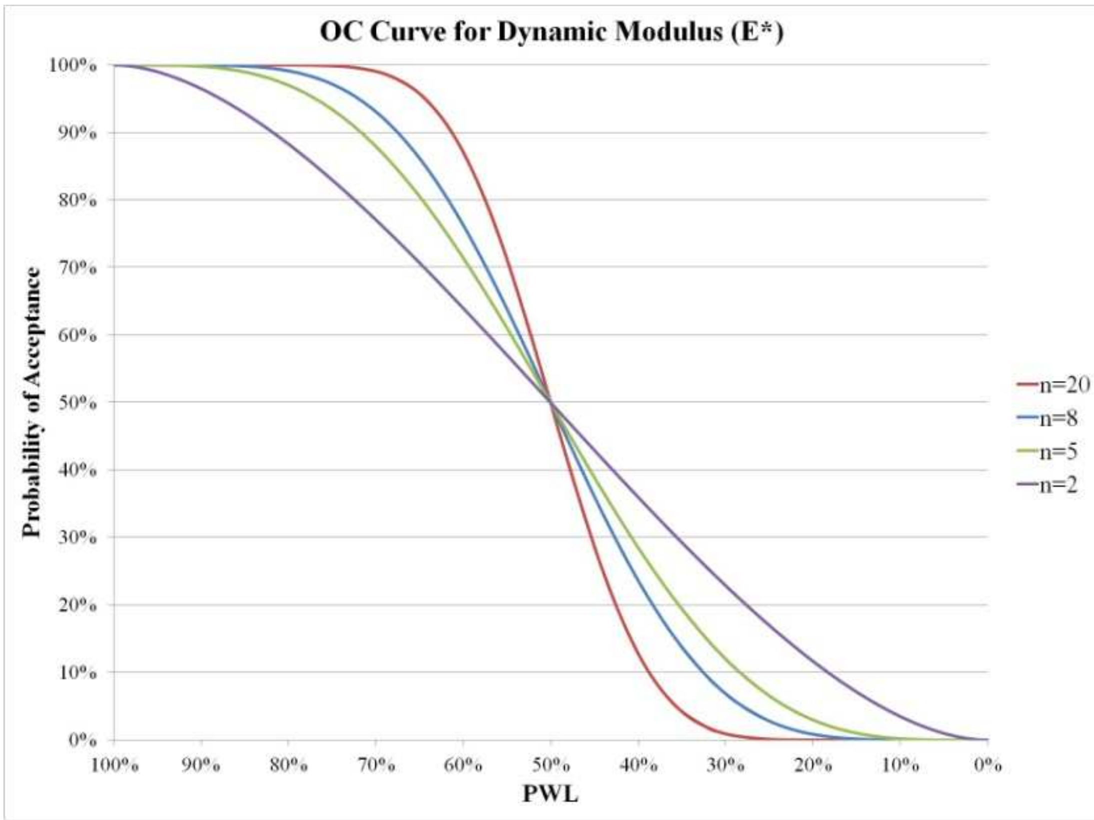


Figure 3.4 OC curves for E* for different sampling sizes

As expected, the OC curves shown in Figure 3.4 approach a step function as the sample sizes increase which translates into the fact that higher sample sizes better represent the true population of the tested material. In statistical terms, a higher sample size results in a lower standard error (SE) hence sample and population characteristics approach the same values.

Equation 3.2 Standard Error Equitation

$$SE = \frac{Standard\ Deviation}{Sample\ Size}$$

After obtaining the OC curves, and in order to translate the curves into risk values, the two parameters of Acceptable Quality Level (AQL) and Rejectable Quality Level (RQL) were set. Commonly used values by state agencies are 90% and 40% for AQL and RQL respectively. Furthermore, since some agencies set AQL at 80%, the value of AQL was decreased to 80% while keeping the RQL constant (at 40%) and the risk values were compared (Table 3.5).

As a result of increasing AQL from 80% to 90%, the Type I risk reduced since increasing the AQL means that the acceptable level of quality at 100% payment is increased and more of the material is within the PWL. Thus, the probability that lower quality material is accepted (i.e., material outside of the specification), is lower.

Table 3.5 Comparison of risks for AQL at 80% and 90%

	AQL=80%, RQL=40%		AQL=90%, RQL=40%	
Sample size (n)	**Type I**	**Type II**	**Type I**	**Type II**
20	0%	13%	0%	13%
8	1%	23%	0%	23%
5	3%	28%	0%	28%
2	11%	36%	3%	36%

In order to translate risk levels to monetary values, the estimated Type I and Type II risk values were related to a pay factor. As the base case, a pay factor introduced by the NCHRP 704 study was considered which is depicted in Figure 3.6. The pay factor for the population characteristics in Table 3.2 (E*=339.2 ksi) was assumed to be at 100% pay as E*=339.2 ksi was the "target value" for the reported lots.

Furthermore, since AQL is assumed to be at 80%, the mean of E* needs to be reduced by 37 ksi so that it results in 80 PWL. Therefore, the mean of E* at AQL is approximately 302.2 ksi (339 ksi target value minus 37 ksi reduction to achieve 80 PWL).

In order to convert E* to a performance measure that is used in design of roadways (i.e., predicted life or Y), Equation 3.3. was used. This equation was proposed from past studies and reported in NCHRP 704. Using equation 3.3, the predicted life (Y) corresponding to when E* = 302.2 ksi is calculated to be 18.13 years.

Equation 3.3 Service Life Prediction for Rutting

$$Y = \frac{\log\left(\left(\frac{RUT}{RUTc} * \frac{E^*}{E^*c}\right)^{2.08662} \left((1+r)^{Yc} - 1\right) + 1\right)}{\log(1+r)}$$

where:

- RUT = rut depth, in inches
- RUT_C = rut depth criterion value, deterministically predicted, in inches
- E^* = dynamic modulus, in ksi
- E^*_c = dynamic modulus criterion value, in ksi
- r = growth rate (rate of traffic increase per year), %
- Y_c = design life, in years
- Y = predicted service life, in years

The following values were recommended in the NCHRP 704 study based on the reported data and previous investigations:

- $RUT_c = 0.5$ in
- $E^* = 302.2$ ksi
- $E^*_c = 374.1$ ksi
- $r = 4\%$
- $Y_c = 20$ years

In order to estimate a value for rut depth (RUT), which is needed as an input to Equation 3.3, a relationship between E* and RUT had to be developed. Per NCHRP 704, a generic form of this relationship is best captured in form of a power function as shown in Equation 3.4 below:

Equation 3.4 Generic form of the function relating E* and RUT

$$RUT = a\,(E^*)^b$$

Therefore, the population data discussed above and as provided by NCHRP 704 was used in order to estimate the best fitting values for a and b in equation 3.4. The result of this curve fitting is shown in Figure 3.5.

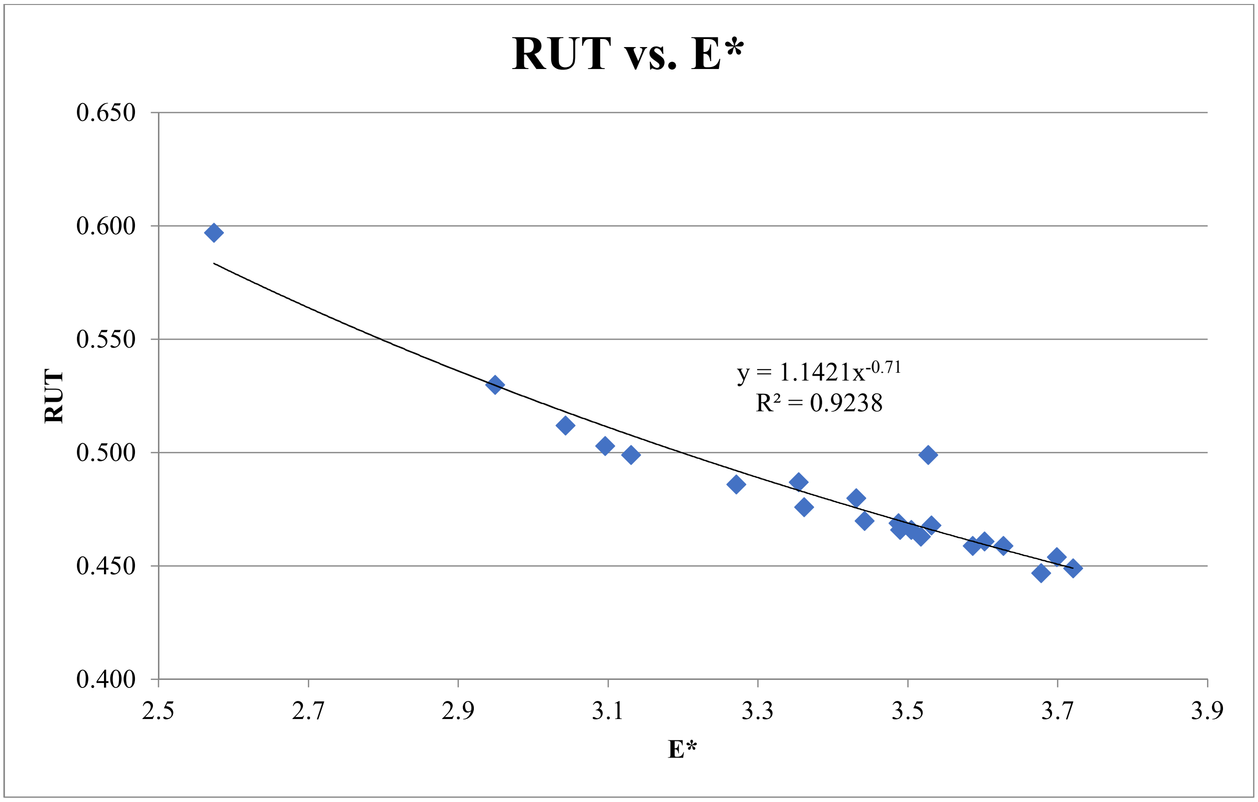


Figure 3.5 Relationship between E* and RUT as prescribed by NCHRP 704

As illustrated in Figure 3.5, the best equation capturing the relationship between E* and RUT for the data used in this study is:

Equation 3.5 Function relating E* and RUT based on NCHRP 704 data

$$RUT = 1.1421\ E^{-0.71}$$

As a result, the RUT value that was used as an input to equation 3.3 is equal to 0.521 inches. For ease of reference, below is the full list of input values into equation 3.3 which as previously noted results in a predicted life (Y) of 18.13 years:

- RUT = 0.521 in
- RUT_c = 0.5 in

- $E^* = 302.2$ ksi
- $E^*_c = 374.1$ ksi
- $r = 4\%$
- $Y_c = 20$ years

Therefore, the difference (ΔY) between the predicted life (Y = 18.13 years) and the design life ($Y_c = 20$) is equal to -1.87 years.

At this stage, it was necessary to relate the performance measure (ΔY) to a monetary value using a pay factor. In order to do so, this study adopted the pay factor depicted in Figure 3.6 which is also the one adopted by NCHRP 704. Based on this pay factor, when $\Delta Y = -1.87$, the lot receives the full payment (i.e., a payment of 100%).

Figure 3.6 Base pay factor model (NCHRP 704)

After estimating the performance and the corresponding pay factor at AQL, it was necessary to do the same for the other end of the spectrum (i.e., at the RQL). In order to do so, the goal was to achieve a PWL of 40% (the RQL). By repeating the same abovementioned process, it was estimated that the mean value of E* needs to be reduced from 339.2 ksi to 265.7 ksi so that PWL = RQL = 40%. Using Equation 3.3 results in a predicted life (Y) of 17.7 years when PWL = RQL = 40%. Therefore, there is a difference of 2.3 years between predicted life and design life (i.e., ΔY=-2.3 years) which based on the pay factor depicted in Figure 3.6, it resulted in a pay factor of 94%.

At this stage of the study, it was necessary to relate the estimated pay factors at AQL and RQL to their corresponding risk levels. By referring to the OC curves in Figure 3.4, it is calculated that for sample size of 8 (n = 8) and when the seller's risk (Type I or α) is 1% (i.e., at AQL) the payment is 100% and when the buyer's risk (Type II or ß) is 23% (i.e., at RQL), the payment is 94%.

From the values estimated and discussed above, it is abundantly clear that there is a significant imbalance of risk levels between the buyer and seller which triggers the need for adjustments in the process, either to the pay factors, the risks levels, or both.

Prior to undertaking any adjustments to the process, it was essential to systematically analyze the risk levels and pay factors at different values of AQL and RQL in order to better understand the dynamics between AQL/RQL with pay factor. The results of such analyses are summarized in Tables 3.6 and 3.7. The results in these tables compare the seller's and buyer's risk at different set of values of RQL and AQL with the corresponding pay factor (PF).

In order to perform these analysis two values were used as the "population mean" of E*:

1- Analysis summarized in Table 3.6 were calculated by considering a population mean of 374.1 ksi for E*. This value was reported as the "target value" of the production lots presented in NCHRP 704. Although this value was set as the target (i.e., the ideal outcome), in average the actual production lots illustrated NCHRP delivered an E* value of 339.2 ksi which represents a more practical population mean.
2- Analysis summarized in Table 3.7 were calculated by considering a population mean of 339.2 ksi for E*. As noted in Table 3.4, this value was obtained by taking the average of the values reported in NCHRP 704.

It is important to note that for the following stages of the study, rather than choosing population characteristics for E*, the population characteristics of individual inputs that constitute the E* equation (Equation 3.1) were considered. Therefore, the analysis in the tables below consider E* as an independent value and does not account for the characteristics of the individual materials and testing input values.

Table 3.6 Risk and Pay Factor Analysis using the target value of simulated lots (from NCHRP 704) as the mean Population Value for E*

	E*(target) = 374.1 ksi, Std. Dev. = 30									
	Population PWL	**Population E***	**Type I Risk**	**Type II Risk**	**Population PF**	**n**	**Sample E***	**Sample Std. Dev.**	**Sample PWL**	**Sample PF**
RQL=	10%	271.1	NA	0%	95%	20	273.0	30.7	49%	96%
RQL=	20%	284.1	NA	0%	99%	20	282.9	28.7	62%	99%
RQL=	30%	293.1	NA	1%	100%	20	293.0	25.3	77%	100%
RQL=	40%	301.1	NA	13%	100%	20	305.2	22.9	91%	100%
AQL/RQL=	50%	309.1	NA	51%	100%	20	314.1	32.0	89%	100%
AQL=	60%	316.6	14%	NA	100%	20	308.6	32.3	86%	100%
AQL=	70%	325.1	1%	NA	100%	20	329.0	22.1	99%	100%
AQL=	80%	334.1	0%	NA	100%	20	340.4	33.4	98%	100%
AQL=	90%	348.1	0%	NA	100%	20	347.5	22.7	100%	100%
AQL=	100%	388.1	0%	NA	100%	20	402.3	25.2	100%	100%
RQL=	10%	271.1	NA	0%	94%	8	277.5	24.2	56%	97%
RQL=	20%	284.1	NA	1%	98%	8	277.0	23.1	55%	97%
RQL=	30%	293.1	NA	7%	100%	8	260.0	25.8	29%	92%
RQL=	40%	301.1	NA	24%	100%	8	291.7	24.7	76%	100%
AQL/RQL=	50%	309.1	NA	50%	100%	8	308.4	32.7	85%	100%
AQL=	60%	316.6	24%	NA	100%	8	305.1	38.5	79%	100%
AQL=	70%	325.1	7%	NA	100%	8	351.0	24.3	100%	100%
AQL=	80%	334.1	1%	NA	100%	8	327.5	23.4	99%	100%
AQL=	90%	348.1	0%	NA	100%	8	347.0	22.5	100%	100%
AQL=	100%	388.1	0%	NA	100%	8	376.0	20.5	100%	100%
RQL=	10%	271.1	NA	0	94%	5	256.1	31.2	28%	91%
RQL=	20%	284.1	NA	3%	98%	5	263.1	19.7	29%	93%
RQL=	30%	293.1	NA	13%	100%	5	300.8	22.7	88%	100%
RQL=	40%	301.1	NA	29%	100%	5	305.4	14.6	98%	100%
AQL/RQL=	50%	309.1	NA	50%	100%	5	294.6	26.6	78%	100%
AQL=	60%	316.6	29%	NA	100%	5	280.1	36.8	57%	98%
AQL=	70%	325.1	12%	NA	100%	5	318.9	39.1	87%	100%
AQL=	80%	334.1	3%	NA	100%	5	308.9	17.3	98%	100%
AQL=	90%	348.1	0%	NA	100%	5	341.8	29.3	99%	100%
AQL=	100%	388.1	0%	NA	100%	5	411.1	36.2	100%	100%
RQL=	10%	271.1	NA	4%	94%	2	306.5	13.0	99%	100%
RQL=	20%	284.1	NA	12%	98%	2	241.6	25.9	10%	87%
RQL=	30%	293.1	NA	23%	100%	2	286.6	10.2	89%	100%
RQL=	40%	301.1	NA	36%	100%	2	310.0	4.4	100%	100%
AQL/RQL=	50%	309.1	NA	50%	100%	2	292.5	67.5	61%	100%
AQL=	60%	316.6	36%	NA	100%	2	301.6	43.3	74%	100%
AQL=	70%	325.1	23%	NA	100%	2	270.8	33.3	46%	95%
AQL=	80%	334.1	11%	NA	100%	2	336.9	8.9	100%	100%
AQL=	90%	348.1	4%	NA	100%	2	324.9	50.1	84%	100%
AQL=	100%	388.1	0%	NA	100%	2	380.0	34.5	100%	100%

Table 3.7 Risk and pay factor analysis using the average value of E* (from NCHRP 704) as the mean population value

	E*(avg of p127) = 339.2 ksi, Std. Dev. = 30										
	Population PWL	**Population E***	**Type I Risk**	**Type II Risk**	**Population PF**	**n**	**Sample E***	**Sample Std. Dev.**	**Sample PWL**	**Δ_Y**	**Sample PF**
RQL=	10%	236.2	NA	0%	85%	20	236.1	32.6	12%	-3.5	85%
RQL=	20%	249.2	NA	0%	89%	20	252.8	31.2	25%	-3.0	90%
RQL=	30%	258.2	NA	1%	92%	20	278.1	44.4	54%	-2.3	97%
RQL=	40%	266.2	NA	12%	94%	20	264.5	36.3	40%	-2.7	93%
AQL/RQL=	50%	274.2	NA	51%	96%	20	275.6	23.5	53%	-2.3	97%
AQL=	60%	281.7	14%	NA	98%	20	279.7	31.6	57%	-2.2	98%
AQL=	70%	290.2	1%	NA	100%	20	291.0	33.8	69%	-1.9	100%
AQL=	80%	299.2	0%	NA	100%	20	296.8	32.6	76%	-1.8	100%
AQL=	90%	313.2	0%	NA	100%	20	314.2	34.6	88%	-1.3	100%
AQL=	100%	353.2	0%	NA	100%	20	343.5	25.8	100%	-0.6	100%
RQL=	10%	236.2	NA	0%	85%	8	234.9	30.2	10%	-3.5	85%
RQL=	20%	249.2	NA	1%	89%	8	252.1	12.6	4%	-3.0	90%
RQL=	30%	258.2	NA	7%	92%	8	268.8	22.9	41%	-2.5	95%
RQL=	40%	266.2	NA	23%	94%	8	269.2	23.6	42%	-2.5	95%
AQL/RQL=	50%	274.2	NA	50%	96%	8	265.1	24.5	36%	-2.6	94%
AQL=	60%	281.7	24%	NA	98%	8	280.6	31.7	58%	-2.2	98%
AQL=	70%	290.2	7%	NA	100%	8	278.2	18.0	59%	-2.3	97%
AQL=	80%	299.2	1%	NA	100%	8	291.5	40.2	67%	-1.9	100%
AQL=	90%	313.2	0%	NA	100%	8	311.4	26.8	92%	-1.4	100%
AQL=	100%	353.2	0%	NA	100%	8	362.1	42.4	98%	-0.2	100%
RQL=	10%	236.2	NA	0	85%	5	229.5	30.5	7%	-3.7	83%
RQL=	20%	249.2	NA	3%	89%	5	239.0	31.2	13%	-3.4	86%
RQL=	30%	258.2	NA	13%	92%	5	270.3	21.0	43%	-2.5	95%
RQL=	40%	266.2	NA	28%	94%	5	257.8	26.4	27%	-2.8	92%
AQL/RQL=	50%	274.2	NA	50%	96%	5	298.4	10.4	99%	-1.7	100%
AQL=	60%	281.7	29%	NA	98%	5	272.6	31.9	48%	-2.4	96%
AQL=	70%	290.2	12%	NA	100%	5	289.7	35.4	67%	-2.0	100%
AQL=	80%	299.2	3%	NA	100%	5	260.3	43.2	37%	-2.8	92%
AQL=	90%	313.2	0%	NA	100%	5	319.7	21.4	98%	-1.2	100%
AQL=	100%	353.2	0%	NA	100%	5	360.5	17.5	100%	-0.2	100%
RQL=	10%	236.2	NA	4%	85%	2	209.6	16.2	0%	-4.3	77%
RQL=	20%	249.2	NA	12%	89%	2	259.7	2.1	0%	-2.8	92%
RQL=	30%	258.2	NA	23%	92%	2	236.3	20.2	3%	-3.5	85%
RQL=	40%	266.2	NA	36%	94%	2	241.4	24.2	9%	-3.3	87%
AQL/RQL=	50%	274.2	NA	50%	96%	2	289.1	7.2	98%	-2.0	100%
AQL=	60%	281.7	36%	NA	98%	2	300.5	52.3	69%	-1.7	100%
AQL=	70%	290.2	23%	NA	100%	2	310.5	34.0	86%	-1.4	100%
AQL=	80%	299.2	11%	NA	100%	2	292.8	23.2	79%	-1.9	100%
AQL=	90%	313.2	4%	NA	100%	2	316.8	9.1	100%	-1.2	100%
AQL=	100%	353.2	0%	NA	100%	2	404.0	31.1	100%	0.8	100%

To better summarize and visualize the results of the analyses presented in Tables 3.6 and 3.7, Figures 3.7 through 3.10, are presented. As illustrated below, the relationship between the determined quality levels (AQL and RQL) is not linear with the corresponding risk types (Type I and Type II). Therefore, it was important to perform such analysis to fully understand the effect of modifying the quality levels.

Furthermore, as expected, the Type II risk may be reduced in two ways:

1- by reducing the RQL
2- by increasing the sample size

Given that reducing the RQL below a certain level is not reasonable, it is upon the agencies to determine the correct balance between sample sizes and the quality levels. Given the same rationale, AQL may not be increased above a certain level and the desired risk level may be achieved by adjusting the sample size.

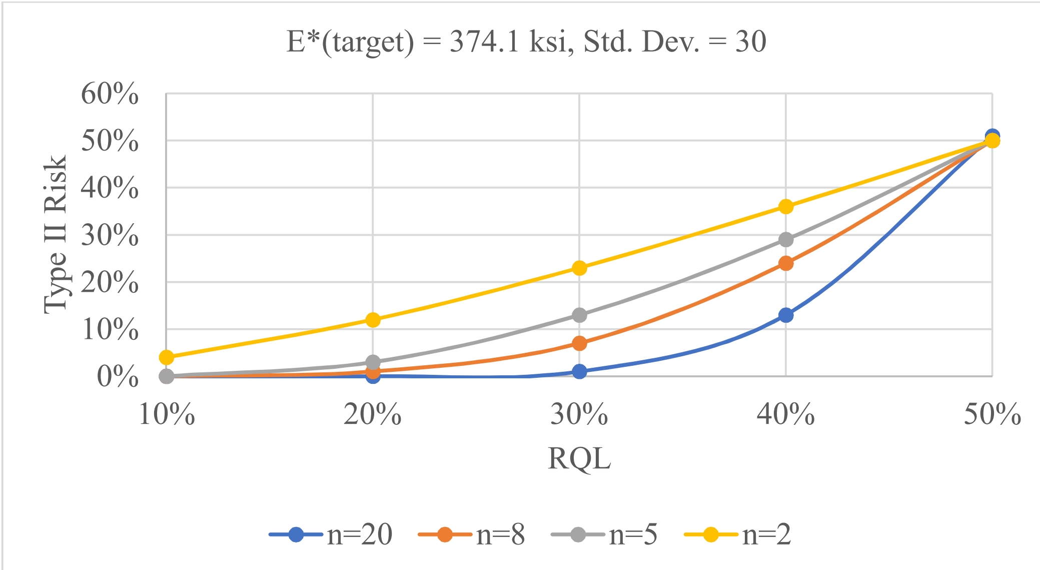


Figure 3.7 Type II risks at different RQL values for E* at target value

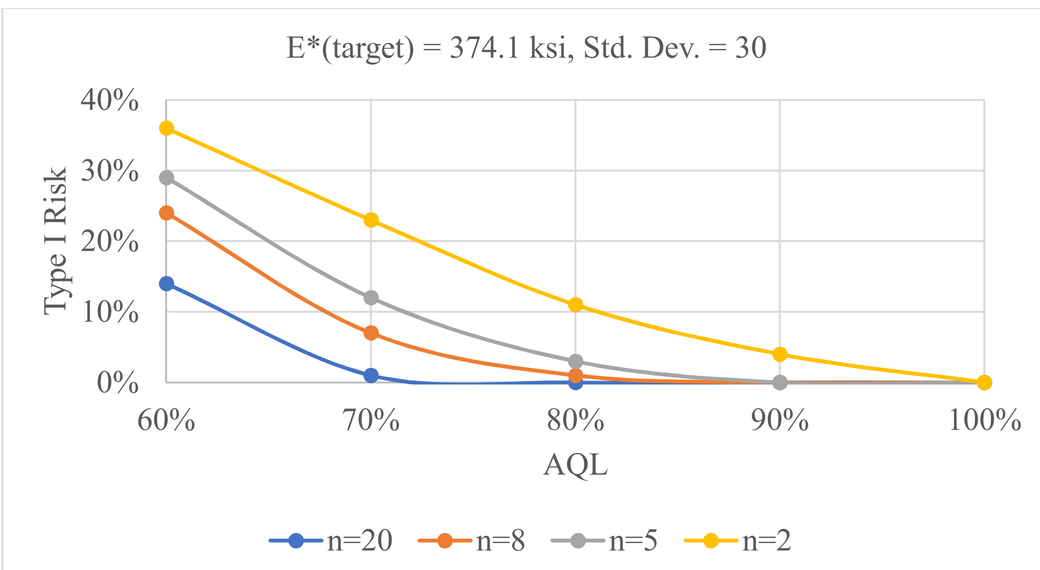


Figure 3.8 Type I risks at different AQL values for E* at target value

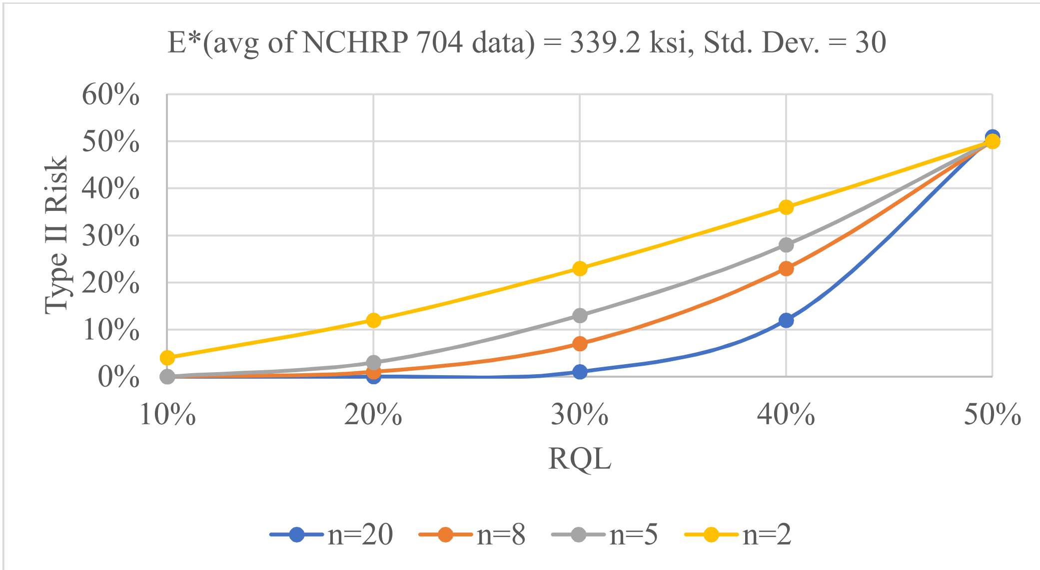


Figure 3.9 Type II risks at different RQL values for E* at average of presented simulated lots

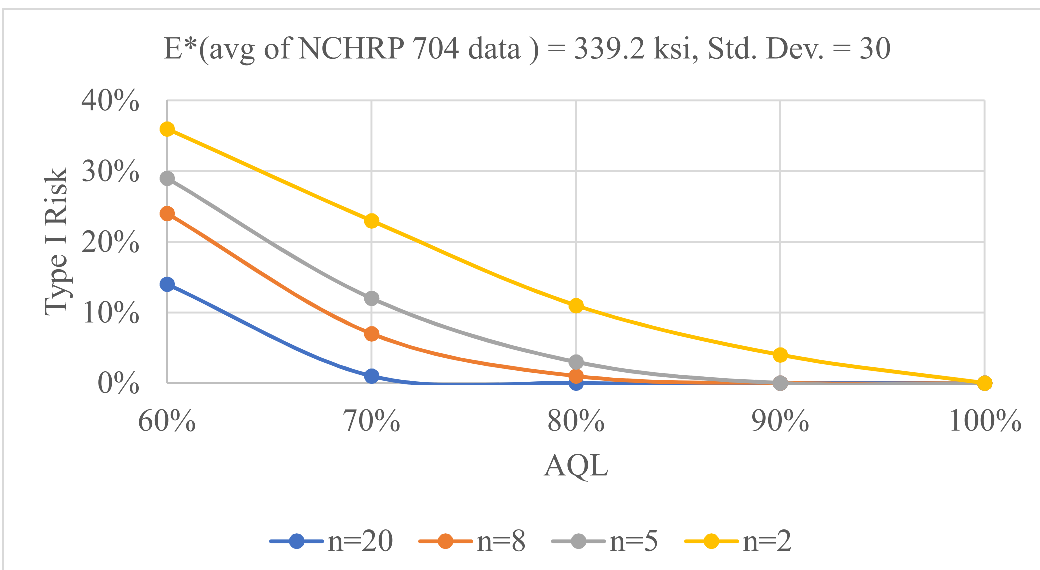


Figure 3.10 Type II risks at different RQL values for E* at average of presented simulated lots

***** THIS PAGE IS INTENTIONALLY LEFT BLANK *****

Chapter 4: Simulation Analysis and Relating Risks to Pay Factors

4.1 Introduction

In the research included in Chapter 3, the risk analysis was based on a range of values for the materials parameters affecting the Dynamic Modulus (E*) which were reported from past studies and the literature. Such analysis provided an initial understanding of the expected acceptance risk levels related the E*. In addition, these analyses provided an understanding of how the sample size pertinent to E* affects Type I and Type II risks.

In order to examine the full range of material parameters affecting E*, it was necessary to identify a distribution for each parameter and employ simulation analysis for generating alternative lots for assessing such effects. Simulation on each material parameter allows estimating Type I and Type II risk levels for each one and ultimately use the results in calculating the combined risk levels of E* and the corresponding pay factor. These analyses also allow to assess and fine tune specification acceptance tolerances for each parameter in order to reach specific levels of risks. In addition, based on such assessment it will be possible to adjust pay factors to reach the desired pay for a given risk level. The details of such analyses and the research findings are presented next.

4.2 Population characteristics

For the simulation analysis there is a need to identify the population distribution for each characteristic of the parameters in interest. As mentioned earlier in the literature review chapter, the typical and most common distribution that several construction material and processes follow is the normal distribution. Therefore, herein the analysis considered a normal distribution for the main six material parameters that affect the Dynamic Modulus (E*).

A normal distribution is defined by two parameters, the mean (μ) and the standard deviation (σ). Table 4.1 tabulates the mean and standard deviation of each of the six material parameters which were obtained from historical data provided by state DOTs and values reported in the NCHRP 704.

Table 4.1 Population characteristics of individual parameters

Parameter	P200	P4	Va	Vbeff	P38	P34
Mean	5.26%	42.05%	7.53%	5.11%	89.14%	100.00%
Std. Dev	0.48	1.96	0.24	0.11	1.37	0.001

Furthermore, it was necessary to identify acceptance tolerances for these mixture parameters representing achievable levels of production quality and producing good/expected HMA performance. In order to do so, tolerances set by two state agencies, Maryland State Highway Administration (MDSHA) and Colorado Department of Transportation (CDOT), and those reported by the American Association of State Highway and Transportation Officials (AASHTO) were considered. Table 4.2 summarizes the reported tolerances which represent common values in the literature by other states as well.

Table 4.2 Mixture Parameter Tolerances

Parameter	**P200**	**P4**	**Va**	**Vbeff**	**P38**	**P34**
Tolerance	±2%	±5%	±0.5%	±0.5%	±6.0%	Max=100% Min=93%
Source	MDSHA	MDSHA	AASHTO	MDSHA	CDOT	CDOT

4.3 Assessment of Acceptance Risks for Dynamic Modulus

As discussed in Chapter 3, AQL and RQL are two components that need to be defined since they affect Alpha (i.e., Type I) and Beta (i.e., Type II) risks. In addition, as it was mentioned in the literature review, previous studies and State Highway Agencies have identified that acceptable AQL and RQL are typically set at 90% and 40% respectively. Furthermore, Alpha and Beta are also tied to the sample size chosen in quality control for each material production lot. While sample size depends on the size of lots and sublots and the number of sublots within a lot, typical values may include a sample size ranging from 6 to 10. For example, for a lot of 6,000 tons, sublots of 1,000 lots are used by MDSHA for assessing production quality and thus n=6 samples are evaluating for accepting or rejecting the lot. Therefore, a range of values for n was considered (encompassing n= 6 and 10) in the analysis. In later stages of the analysis, and as discussed in detail in chapter 5, the sample size is one of the parameters adjusted in order to achieve a desired level of risk levels and the corresponding pay factors.

In order to simulate the lots and sublots of E* values, each of the six parameters that constitute Equation 3.1 were simulated using the characteristics in Table 4.1.

500,000 simulations were performed of each parameter in order to be as close to the true population as possible considering the computing power available. The simulated values of each parameter resulted in 500,000 E* values (by utilizing equation 3.1). Furthermore, per AASHTO PP62, a tolerance of ±13% was selected as the upper and lower bounds of E* values which was used to calculate the percentage of sublots that fall within the set tolerance. However, based on the sample data obtained from NCHRP 704 report, using the ±13% tolerance results in a PWL of 88.6% for the population characteristics detailed in Table 3.4 which makes it impossible to achieve an AQL of 90%. Therefore, the tolerances were adjusted from ±13% to ±15% in order to accommodate for this.

As discussed previously, Type I and Type II risks are calculated at the predefined AQL and RQL and for different sample sizes. Table 4.3 presents a summary of the risk levels with different sample sizes pulled from the 500,000 simulated values of E*, tolerances of ±15%, AQL of 90% and RQL of 40%.

Table 4.3 Alpha and Beta values at different sample sizes of E*

Sample Size	20	10	8	6	4	2
Alpha (Type I)	0.000%	0.001%	0.007%	0.049%	0.355%	2.907%
Beta (Type II)	12.9%	21.2%	23.7%	26.8%	30.6%	36.0%

As expected, by increasing the sample size, the aggregate of the representative samples is expected to have properties closer to the true population value, which results in lower risk levels for both the agency and the contractor. Therefore, if an agency was aiming to set a sample size per each lot when calculating E*, Table 4.3 can provide guidance on what levels of risks are to be expected at each n. Vice versa, if the highway agency wants to reduce risks, a higher number of samples are needed to judge the acceptance of materials.

However, at typical sample sizes (n=4 to 6), the risk levels tabulated in Table 4.3 are significantly imbalanced and although the seller's risk level is reasonably close to the suggested values by AASHTO, for the buyer (Beta) it is above accepted guidance set by AASHTO (refer to Table 4.5). This observation makes it imperative to relate a tangible performance criterion to a monetary value and balance both risks. Therefore, in the next sections it is examined how to relate the Dynamic Modulus to a performance criterion.

4.4 Performance criteria

When designing a pavement structure, the highway agency aims for a certain number of years of service, which in turn dictates other properties of the pavement. Therefore, a reasonable and common way of measuring the quality of a constructed pavement is to compare the predicted years that it will be in service based on the construction quality compared to the target number of years according to design.

As briefly discussed in Chapter 3, various studies, including NCHRP 704, proposed performance prediction models that predict the life of a pavement given certain construction characteristics and materials' properties. For example, in NCHRP 704 the Dynamic Modulus was related to pavement rutting, and consequently rutting to service life. In order to accomplish this relationship, many mixtures were selected and tested under different conditions. The results have shown that the best model to relate E* to rutting (RUT) is a power function.

Equation 3.5 and Figure 3.5 are repeated below to illustrate how a typical rutting prediction model was used in this analysis. As shown in Figure 4.1, the power function turns out to be a good fit to the data with an R^2=92%.

Equation 4.1 Function relating E* and RUT based on NCHRP 704 data

$$RUT = 1.1421\ E^{-0.71}$$

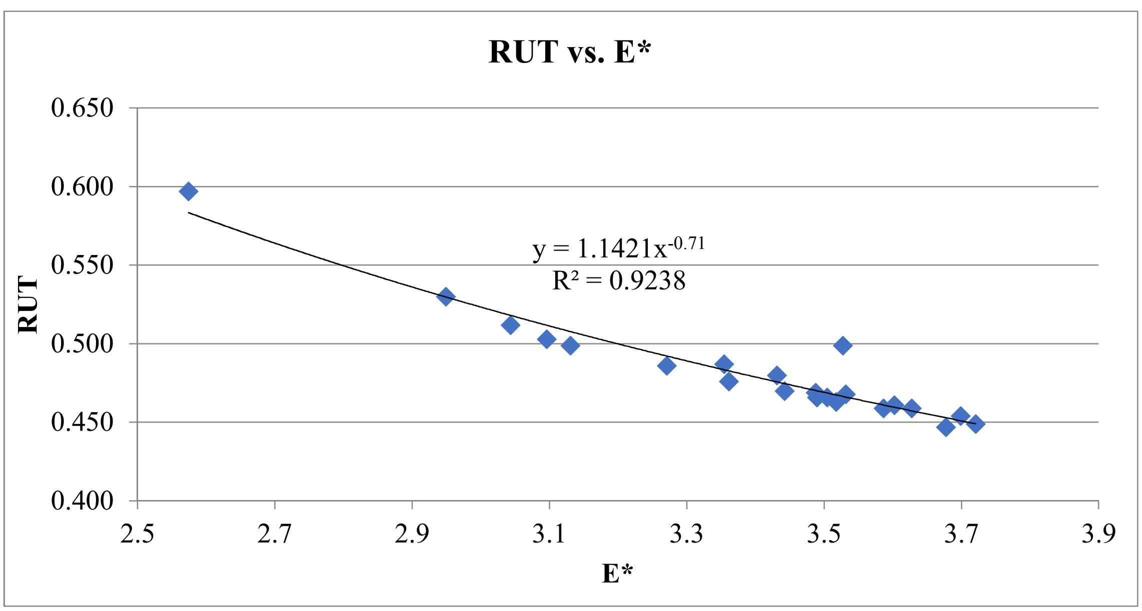


Figure 4.1 Relationship between E* and RUT as prescribed by NCHRP 704

As also discussed in Chapter 3 (equation 3.3), NCHRP 704 has provided the means of relating the RUT value to the service life using Equation 4.2 below:

Equation 4.2 Service Life Prediction for Rutting

$$Y = \frac{\log\left(\left(\frac{RUT}{RUTc} * \frac{E^*}{E^*c}\right)^{2.08662}((1+r)^{Yc} - 1) + 1\right)}{\log(1+r)}$$

where:

- RUT = rut depth, in inches
- RUT_C = rut depth criterion value, deterministically predicted, in inches
- E^* = dynamic modulus, in ksi
- E^*_c = dynamic modulus criterion value, in ksi
- r = growth rate (rate of traffic increase per year), %
- Y_c = design life, in years
- Y = predicted service life, in years

As described in NCHRP 704: “this relationship was developed using empirical data to relate the predicted distress to the pavement life, which is then used to estimate the pavement life for the as-designed mix. To assess the impact of the difference in the distress predictions, the service life of the pavement is calculated using the equation for rutting.”

Table 4.4 below tabulates the values considered for each parameter in, as recommended by NCHRP 704, and also noted in Chapter 3:

Table 4.4 Assumed values for calculating the predicted service life

Parameter	Value	Unit	Source
Y_c	20	Year	NCHRP704
RUT_c	0.5	Inch	NCHRP704
E^*_c	3.741	psi	NCHRP704
1+r	1.040	%	US DOT

Based on the Equation 3.1, 4.1 and 4.2, the HMA mixture parameters, such as sieve parameters, percent air voids, loading frequency, bitumen viscosity and effective bitumen content, were thus related to a measurable performance criterion - the predicted service life. In the following analysis, such approach was used to examine and reach desirable risk levels between the producer and the agency while monitoring the monetary implications in order to provide acceptable pay factor.

4.5 Aiming for certain α and β risk level

The first approach in order to balance the risk between the seller and the agency is to aim for certain levels of risk and modify the process in order to achieve them. As tabulated in Table 4.5, AASHTO R-9 has recommended the following levels of risk for construction projects.

Table 4.5 Recommended risk levels by AASHTO R-9

Criticality	Recommended α	Recommended β
Critical	0.050	0.005
Major	0.010	0.050
Minor	0.005	0.100
Contractual	0.001	0.200

According to AASHTO R-9, the criticality of the project is defined as:

Critical: when the requirement is essential to preservation of life.

Major: when the requirement is necessary for prevention of substantial financial loss.

Minor: when the requirement does not materially affect performance.

Contractual: when the requirement is established only to provide uniform standards for bidding.

A "major" level of criticality was assumed for this study. However, each agency needs to pre-determine the criticality level of the project in relation to the potential implications of a possible failure on a case-by-case basis.

4.6 Adjusting the sample size (n)

It is common practice for agencies to define the number of samples based on statistical criteria and in function of lot/sublot size and production variability. Therefore, the first attempt in achieving the desired risk levels is adjusting sample size. The effect of sample size was discussed in Chapter 3, Section 3.3 *Type I and II risk of Dynamic Modulus vs. pay factor*. However, it is important to note that achieving $\alpha = 1\%$ and $\beta=3\%$ (obtained from AASHTO R-9) simultaneously for E* is not possible by only changing the sample size. For example, by repeating the analysis tabulated in table 4.3, one must set n = 3 in order to achieve $\alpha = 1\%$ which will result in $\beta = 33\%$ which is well above the desired 5%. Furthermore, in order to achieve $\beta = 5\%$ the sample size must be increased to 42 which is not a practical sample size from. Table 4.6 below amends table 4.3 with when sample size is set at 3 and 42.

Table 4.6 Alpha and Beta values at different sample sizes of E*

Sample Size	42	20	10	8	6	4	3	2
Alpha (Type I)	0.00%	0.00%	0.00%	0.01%	0.05%	0.36%	1.00%	2.91%
Beta (Type II)	5.00%	12.9%	21.2%	23.7%	26.8%	30.6%	33.0%	36.0%

4.7 Adjusting the tolerances

The next step was to adjust the specification tolerances on each input material and mixture parameter in order to achieve the desired risk levels for E*. Although this adjustment could be approached as a multivariable problem, this study looks at the effects of each parameter individually considering the effects and minimal impact of correlation between these variables discussed in an earlier section. In Chapter 5, a step-by-step multivariate adjustment is also considered. Furthermore, it is important to note that highway agencies and contractors are able to deal with the approach of assessing the effects of each parameter one at a time than dealing with a multivariate optimization problem that may become mathematically and computationally challenging.

The necessary steps for adjusting specification tolerances are presented in the FHWA study *"Optimal Procedures for QA Specifications"* by Burati et. al. (2003). The analysis involves the following steps:

1- Identify AQL and RQL that correspond to the desired alpha and beta respectively (e.g., alpha = 1% and beta = 5%).

2- For each AQL and RQL value obtained in step 1, find the respective Z-Score value using the readily available Z-Score charts.

3- Multiply the Z-value by the standard deviation of the representative lot.

Applying the abovementioned process to each material and mixture parameter that constitutes E* (Equation 3.1) results in the tolerances of Table 4.7.

Table 4.7 New specification tolerances for individual parameters

Property	Tolerance	AQL @ α= 1%	RQL @ β = 5%	Mean @ AQL	Std. Dev.	Z-Score	**New Tol**
P200	±2%	81.312%	25.087%	5.55%	0.484	0.43	**±0.21%**
P4	±5%	82.886%	25.095%	38.91%	1.959	1.86	**±3.64%**
Va	±0.5%	82.838%	25.095%	7.81%	0.236	0.22	**±0.05%**
Vbeff	±0.5%	82.887%	25.095%	4.72%	0.114	0.11	**±0.01%**
P38	±6.0%	82.887%	25.095%	93.84%	1.366	1.30	**±1.77%**
P34	UL 100 LL 93	82.887%	25.095%	100.00%	0.001	0.00	**0.00%**

As shown in Table 4.6, in some instances the tolerance needs to be reduced 10 times in order to achieve the desired risk levels. Such levels of high quality and low production variability requires great improvements in construction technology, and perhaps for most parameters this may not be feasible at this time. As discussed later in Chapter 5, a possible approach to addressing this issue, is performing a step-by-step multivariate analysis. It is important to note that if the new tolerances of this analysis were judged to be achievable and cost-justified, the producers would adjust production of each parameter to have a distribution with a mean equal to the new "Mean @ AQL" column in Table 4.7. For example, if the new tolerance of ±3.64% was achievable for P4, the producer would have to produce material that have a P4 distribution with mean of

38.91% ("Mean at AQL"). The effect of changing the standard deviation by the producer is discussed in the following sections.

To examine the effects of the new tolerances on E*, a new population of E* was simulated using the same analysis steps discussed earlier in this chapter. This required using the new means shown in Table 4.7 and the same standard deviations tabulated in Table 4.1.

The new simulated population of E* (using the new means tabulated in Table 4.7) has a mean of 262.7 ksi and standard deviation of 31 ksi. By applying the recommended ±13% tolerance to this new population of E*, the maximum achievable PWL at the upper limit of the tolerance is 57.9%. Therefore, with tolerances calculated for individual inputs, the new population of E* exposes a significantly higher risk (when setting $n = 8$) to the contractor ($\alpha = 31.5\%$) while the agency risk is unchanged. This can be better observed by looking at the OC Curve in Figure 3.4 and also illustrated in Figure 4.2.

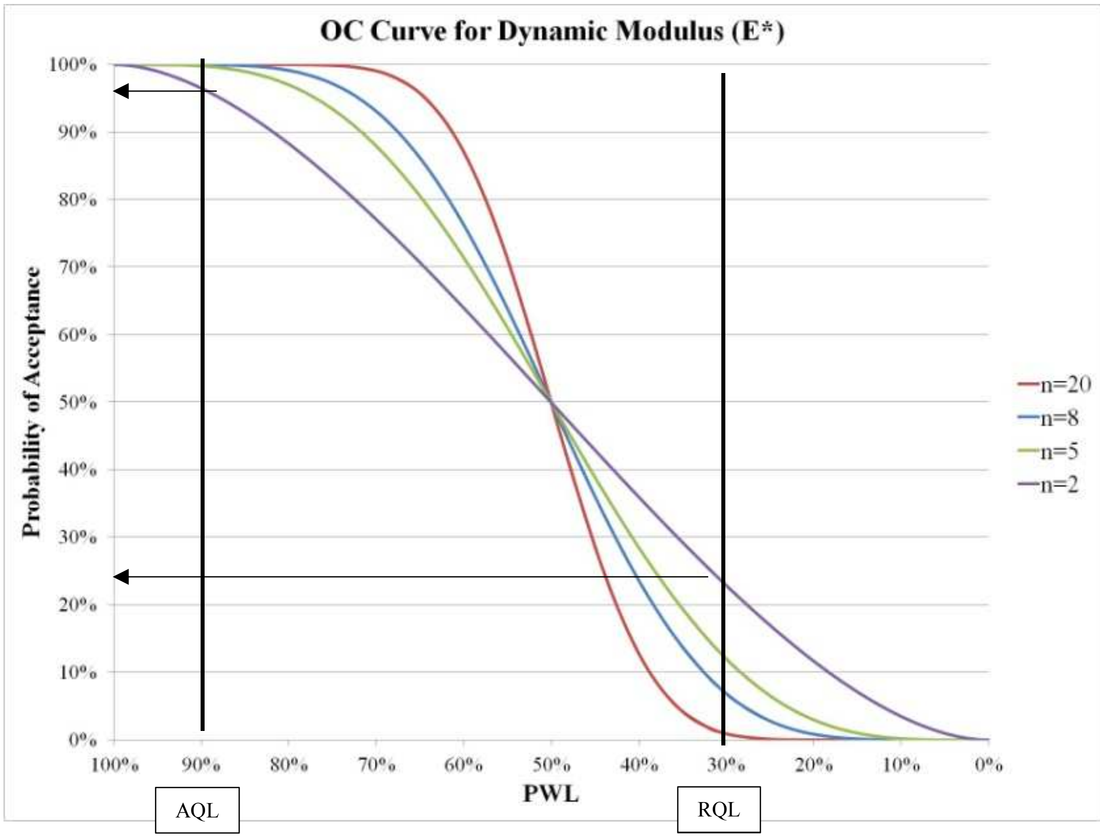


Figure 4.2 OC curves for E* for different sampling sizes

Therefore, the next step would be to adjust the tolerance of E* to achieve 90 PWL at AQL and then find the mean where PWL = AQL. In order to achieve PWL = AQL = 90% the tolerance has to be increased from 13% to 27% which is more than a 100% increase.

In summary, with the current production quality, it is required to increase the tolerances of E* from 13% to a tolerance of 27% in order to achieve the risk levels recommended by AASHTO R-9. In practice, this will lead to producers relaxing their production quality and resulting in much higher variability of production, which is not the desired outcome for either party.

4.8 Sensitivity analysis on the population pay factor

In the prior sections it was possible to demonstrate the necessary process in order to achieve the desired risk levels for the seller and buyer. As discussed in the objectives of the study, it is of interest to be able to relate risk levels to monetary values. Such a relationship will allow the agencies to decide what level of risk is desired while taking into consideration the cost of achieving those risk levels. It will also allow them to fine tune the specifications and PF in relation to the desired levels of risks.

The first step in this process is to find the parameters that the pay factor is most sensitive to. Based on the pay factor illustrated in Figure 3.5 of Chapter 3, the effect of changing the mean of each input parameter by a certain percentage to the overall pay value was examined. As discussed previously, 500,000 lots of each parameter were simulated given the population characteristics discussed earlier which ultimately results in 500,000 values of E*. The results of this sensitivity analysis are tabulated in Tables 4.8, 4.9 and 4.10.

Table 4.8 Sensitivity analysis on pay factor by adjusting the mean of P200, P4, Va and Vbeff parameters by ±5%

Parameter	+5% Mean		-5% Mean	
	New PF	% Change	New PF	% Change
P200	100	0.0%	100	0.0%
P4	99.9	-0.1%	100	0%
Va	99.9	-0.1%	100	0%
Vbeff	99.9	-0.1%	100	0%

Table 4.9 Sensitivity analysis on pay factor by adjusting the mean of P200, P4, Va and Vbeff parameters by ±20%

Parameter	+20% Mean		-20% Mean	
	New PF	% Change	New PF	% Change
P200	100	0.0%	99.9	-0.1%
P4	99.5	-1%	99.9	0%
Va	98.6	-1%	99.1	-1%
Vbeff	99.5	-1%	99.1	-1%

Table 4.10 Sensitivity analysis on pay factor by adjusting the mean of P200, P4, Va and Vbeff parameters by ±50%

Parameter	+50% Mean		-50% Mean	
	New PF	% Change	New PF	% Change
P200	100	0.0%	99.3	-0.7%
P4	92.7	-7%	78.6	-21%
Va	78.4	-22%	87.4	-13%
Vbeff	95.1	-5%	51.5	-49%

For the P_{38} and P_{34} variables, since the values cannot go above 100%, the scenario with ±20% change in the mean was replaced by ±10% change. In addition, the +50% change in the mean is labeled as "NA" since the mean value of P_{39} and P_{34} would be above 100%. The results are shown in Tables 4.11, 4.12 and 4.13.

Table 4.11 Sensitivity analysis on pay factor by adjusting the mean of P38 and P34 parameters by ±5%

Parameter	+5% Mean		-5% Mean	
	New PF	% Change	New PF	% Change
P38	93.4	-6.6%	86.1	-14%
P34	NA	NA	99.8	0%

Table 4.12 Sensitivity analysis on pay factor by adjusting the mean of P38 and P34 parameters by ±10%

Parameter	+10% Mean		-10% Mean	
	New PF	% Change	New PF	% Change
P38	63.8	-36%	29.4	-71%
P34	NA	NA	99.3	-1%

Table 4.13 Sensitivity analysis on pay factor by adjusting the mean of P38 and P34 parameters by ±50%

Parameter	+50% Mean		-50% Mean	
	New PF	% Change	New PF	% Change
P38	NA	NA	110	10%
P34	NA	NA	52.6	-47%

Furthermore, the effect of changing the standard deviation of each parameter on the pay factor was also analyzed. As expected, no change is observed. This result has also mathematical intuition since by keeping the mean constant and changing the standard deviation it is only widening the distribution but not changing the average value for which PF is based on. For example, if the mean of V_a is increased by 50%, the new distribution of V_a will have a mean of 11.30% and a standard deviation of 0.24. As shown in Table 4.10 an increase of 50% in the mean of Va, results in a -22% change in the total PF. On the other hand, if the standard deviation is increased by 50% but the mean is unchanged, the distribution of V_a will have the same mean (7.53% as shown in Table 4.1) and a standard deviation of 0.36 (obtained by multiplying the population standard deviation of 0.24 as reported in Table 4.1, by 1.5). In addition, since the example PF equation (Figure 3.6) takes a single value of performance (Y) and therefore a single value of Va which constitutes E* (equation 3.1), enough samples have to be simulated in order to capture characteristics of the population. Therefore, the single value of the Va population that enters equation 3.1 to estimate an E* and ultimately the Y that the PF equation (Figure 3.6) takes as an input is its mean and the change standard deviation does not affect the final PF value.

As shown in the tables above, the assumed pay factor has the highest sensitivity to changes in the mean value of P_{38} regardless of the magnitude and sign (+ or -) of the change among all of the parameters that contribute to the estimation of E*. In addition, given the non-linear equation of E*, equation 3.1, the pay factor's sensitivity to the other parameters depends on the direction/sign and the magnitude of the percent change. For example, regardless of whether the Va mean value is increased or decreased by 50%, the PF is decreased, Table 4.10, since there are more production lots falling outside the speciation tolerances. In the case of increasing the mean by 50%, the normal distribution of the parameter shifts to the right causing more of the distribution to fall outside of the upper limit. In case of decreasing the mean by 50%, the normal distribution of the parameter shifts to the left causing more of the distribution falling outside of the lower limit. Furthermore, since the value of the population pay factor is calculated by averaging the pay factor of all simulations, the changes in the standard deviation do not result in change of the pay factor.

4.9 Sensitivity analysis on risks

It is also important to test how sensitive the risks associated with each parameter are to changes in the distribution of each individual parameter. Changing the standard deviation of each material parameter does not affect the overall pay factor. As described in the previous section, this is due to the fact that although the parameter distributions become wider, their average/mean value is not affected.

The effects of changing the standard deviation of each parameter on the associated risk were analyzed and summarized in Tables 4.14 to 4.19.

Table 4.14 Sensitivity analysis of Alpha risk of individual parameters by adjusting the std. dev. by ±5%

	+5% Std. Dev		-5% Std. Dev	
Parameter	New α	% Change	New α	% Change
P200	0.0847%	0.0%	0.0847%	0.0%
P4	0.0840%	-0.5%	0.0846%	0.2%
Va	0.0730%	-7.0%	0.0818%	4.2%
Vbeff	0.0847%	0.0%	0.0847%	0.0%
P38	0.0847%	0.0%	0.0847%	0.0%
P34	NA	NA	NA	NA

Table 4.15 Sensitivity analysis of Alpha risk of individual parameters by adjusting the std. dev. by ±20%

	+20% Std. Dev		-20% Std. Dev	
Parameter	New α	% Change	New α	% Change
P200	0.0847%	0.0%	0.0847%	0.0%
P4	0.0789%	-6.6%	0.0847%	0.3%
Va	0.0378%	-51.8%	0.0846%	7.8%
Vbeff	0.0847%	0.0%	0.0847%	0.0%
P38	0.0847%	0.0%	0.0847%	0.0%
P34	NA	NA	NA	NA

Table 4.16 Sensitivity analysis of Alpha risk of individual parameters by adjusting the std. dev. by ±50%

	+50% Std. Dev		-50% Std. Dev	
Parameter	New α	% Change	New α	% Change
P200	0.0847%	-0.1%	0.0847%	0.0%
P4	0.0224%	-73.4%	0.0847%	0.3%
Va	NS	NS	0.0847%	7.9%
Vbeff	0.0847%	0.0%	0.0847%	0.0%
P38	0.0847%	0.0%	0.0847%	0.0%
P34	NA	NA	NA	NA

Table 4.17 Sensitivity analysis of beta risk of individual parameters by adjusting the std. dev. by ±5%

	+5% Std. Dev		-5% Std. Dev	
Parameter	New β	% Change	New β	% Change
P200	26.7441%	0.0%	26.7441%	0.0%
P4	26.7441%	0.0%	26.7441%	0.0%
Va	26.7459%	0.0%	26.7444%	0.0%
Vbeff	26.7441%	0.0%	26.7441%	0.0%
P38	26.7441%	0.0%	26.7441%	0.0%
P34	NA	NA	NA	NA

Table 4.18 Sensitivity analysis of beta risk of individual parameters by adjusting the std. dev. by ±20%

	+20% Std. Dev		-20% Std. Dev	
Parameter	New β	% Change	New β	% Change
P200	26.7440%	0.0%	26.7441%	0.0%
P4	26.7448%	0.0%	26.7441%	0.0%
Va	26.7600%	0.1%	26.7441%	0.0%
Vbeff	26.7441%	0.0%	26.7441%	0.0%
P38	26.7441%	0.0%	26.7442%	0.0%
P34	NA	NA	NA	NA

Table 4.19 Sensitivity analysis of beta risk of individual parameters by adjusting the std. dev. by ±50%

	+50% Std. Dev		-50% Std. Dev	
Parameter	New β	% Change	New β	% Change
P200	26.7441%	0.0%	26.7441%	0.0%
P4	26.7702%	0.1%	26.7441%	0.0%
Va	26.9622%	0.8%	26.7441%	0.0%
Vbeff	26.7440%	0.0%	26.7441%	0.0%
P38	26.7441%	0.0%	26.7441%	0.0%
P34	NA	NA	NA	NA

Finally, the effect of modifying the standard deviation of each material parameter on the overall risk (i.e., risk associated with dynamic modulus) was also assessed in Tables 4.20 to 4.25 for a sample size n=6.

Table 4.20 Sensitivity analysis of alpha risk of dynamic modulus (E*) by adjusting std. dev. of each parameter by ±5%

	+5% Std. Dev		-5% Std. Dev	
Parameter	New α	% Change	New α	% Change
P200	0.0494%	1.1%	0.0495%	1.3%
P4	0.0478%	-2.2%	0.0499%	2.1%
Va	0.0479%	-1.9%	0.0492%	0.7%
Vbeff	0.0489%	0.1%	0.0497%	1.8%
P38	0.0346%	-29.2%	0.0607%	24.3%
P34	NA	NA	NA	NA

Table 4.21 Sensitivity analysis of alpha risk of dynamic modulus (E*) by adjusting std. dev. of each parameter by ±20%

	+20% Std. Dev		-20% Std. Dev	
Parameter	New α	% Change	New α	% Change
P200	0.0461%	-5.6%	0.0526%	7.6%
P4	0.0443%	-9.3%	0.0544%	11.4%
Va	0.0449%	-8.0%	0.0521%	6.7%
Vbeff	0.0485%	-0.7%	0.0496%	1.6%
P38	NS	NS	0.0798%	63.4%
P34	NA	NA	NA	NA

Table 4.22 Sensitivity analysis of alpha risk of dynamic modulus (E*) by adjusting std. dev. of each parameter by ±50%

	+50% Std. Dev		-50% Std. Dev	
Parameter	New α	% Change	New α	% Change
P200	0.0414%	-15.2%	0.0525%	7.5%
P4	0.0299%	-38.8%	0.0587%	20.2%
Va	0.0338%	-30.7%	0.0579%	18.5%
Vbeff	0.0447%	-8.6%	0.0526%	7.6%
P38	NS	NS	0.0847%	73.4%
P34	NA	NA	NA	NA

Table 4.23 Sensitivity analysis of beta risk of dynamic modulus (E*) by adjusting std. dev. of each parameter by ±5%

	+5% Std. Dev		-5% Std. Dev	
Parameter	New β	% Change	New β	% Change
P200	26.7541%	0.0%	26.7541%	0.0%
P4	26.7548%	0.0%	26.7539%	0.0%
Va	26.7548%	0.0%	26.7542%	0.0%
Vbeff	26.7543%	0.0%	26.7539%	0.0%
P38	26.7613%	0.0%	26.7496%	0.0%
P34	NA	NA	NA	NA

Table 4.24 Sensitivity analysis of beta risk of dynamic modulus (E*) by adjusting std. dev. of each parameter by ±20%

	+20% Std. Dev		-20% Std. Dev	
Parameter	New β	% Change	New β	% Change
P200	26.7556%	0.0%	26.7527%	0.0%
P4	26.7565%	0.0%	26.7520%	0.0%
Va	26.7562%	0.0%	26.7529%	0.0%
Vbeff	26.7545%	0.0%	26.7540%	0.0%
P38	26.8157%	0.2%	26.7446%	0.0%
P34	NA	NA	NA	NA

Table 4.25 Sensitivity analysis of beta risk of dynamic modulus (E*) by adjusting std. dev. of each parameter by ±50%

	+50% Std. Dev		-50% Std. Dev	
Parameter	New β	% Change	New β	% Change
P200	26.7580%	0.0%	26.7527%	0.0%
P4	26.7649%	0.0%	26.7503%	0.0%
Va	26.7624%	0.0%	26.7506%	0.0%
Vbeff	26.7563%	0.0%	26.7528%	0.0%
P38	27.2508%	1.9%	26.7441%	0.0%
P34	NA	NA	NA	NA

As observed from the analysis in tables 4.14 through 4.25, both the individual and overall risks are most sensitive to the Va parameter. For example, increasing the standard deviation of Va by 20% results in a 51.8% decrease in the value of alpha (Table 4.15) whereas the next most sensitive parameter (Pa) results in only a 6.6% decrease (Table 4.15). However, it is important to note that although the % change seems significant, the risk levels are minimally small and close to zero. Furthermore, it is important to note that changing the mean has no effect on the risk levels since the risk levels are always estimated when the distribution of the parameter is shifted so that the mean of the distribution is either at AQL (for alpha) or RQL (for beta). However, as illustrated in the OC curves (Figure 4.2) risk levels are affected by the sample size. In other words, the higher the number of samples the lower the standard deviation difference between the samples and the population, and thus the lower the risk as it can be seen from Figure 4.2. This becomes more apparent when the same analysis is conducted for Beta risks (Tables 4.17, 4.18, 4.19, 4.23, 4.24, and 4.25). The % changes are insignificant across the board as the Beta values themselves are large numbers compared to alpha values (26% vs. 0.05%).

This analysis illustrated that modifying the production standard deviation (i.e., production quality in terms of material homogeneity) in trying to control acceptance risks provides minimal results.

4.10 Overall findings

In the analysis presented in Section 4.5, typical population characteristics of parameters that constitute E* were used as reported by past studies, and the goal was to assess how adjusting the tolerances (which is indirectly related to the standard deviation) and sample size will affect resulting acceptance risk levels. It was observed that by increasing the sample size, (in statistical terms this implies that the lot/sublot samples are expected to represent better estimates of the true population characteristics), results in lower risk for both the agency and the contractor.

In the analysis of sections 4.7 and 4.8, both the mean and standard deviation of each material parameter were adjusted in order to assess the sensitivity of the overall pay factor (i.e., related to E*). The results showed that the pay factor has the highest sensitivity to changes in the mean value of P38 regardless of the magnitude and sign (+ or -) of the change among all the parameters that contribute to the estimation of E*. In addition, given the non-linear equation of E*, the pay factor's sensitivity to the remaining parameters depends on the direction/sign and the magnitude of the change. Lastly, it was shown that the overall risks are most sensitive to changes in the Va parameter.

***** THIS PAGE IS INTENTIONALLY LEFT BLANK *****

Chapter 5: Recommended Approach to Balancing Risks and Pay Factors

5.1 Introduction

In chapters 3 and 4 it was explored how the risk levels relate to: the mean and standard deviation of the parameters constituting E*; the effects on the suggested pay factor function suggested in the NCHRP 704 national study; and specification tolerances considering specific levels of AQL and RQL. It was the objective of the analysis herein to further examine the relation between pay factors and risks in order to recommend a generalized approach for balancing risks and pay factors that can be applied to similar construction materials acceptance criteria.

5.2 General methodology and analysis steps for assessing pay factors and risks

Based on the analysis and the findings conducted so far, this section assembles an expansive step-by-step process to follow in order to review the current state of affairs and identify the available options for balancing acceptance risks and pay factors. The flow chart of Figure 5.1 represents the summary of the suggested methodology followed by detailed explanation of each step.

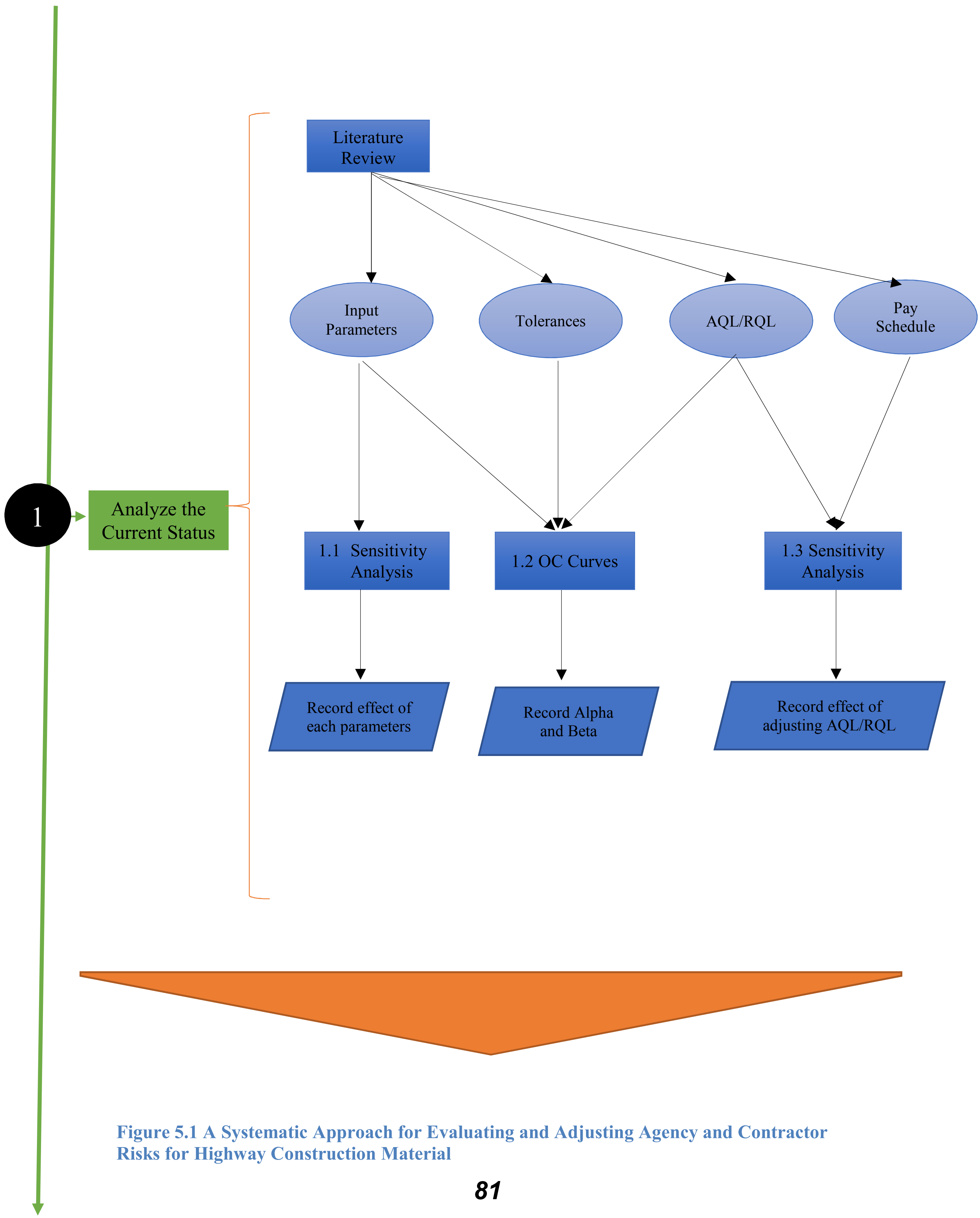


Figure 5.1 A Systematic Approach for Evaluating and Adjusting Agency and Contractor Risks for Highway Construction Material

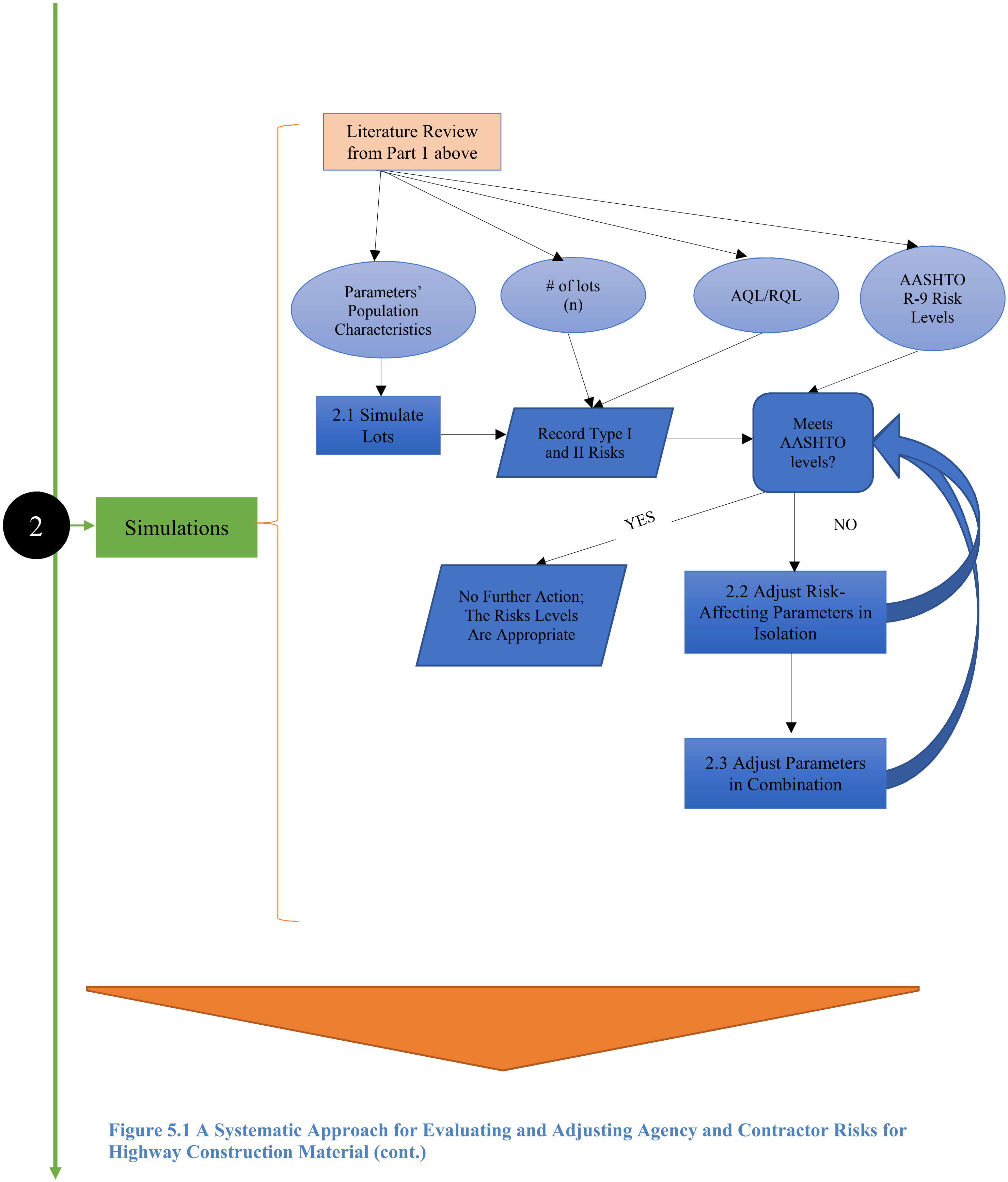


Figure 5.1 A Systematic Approach for Evaluating and Adjusting Agency and Contractor Risks for Highway Construction Material (cont.)

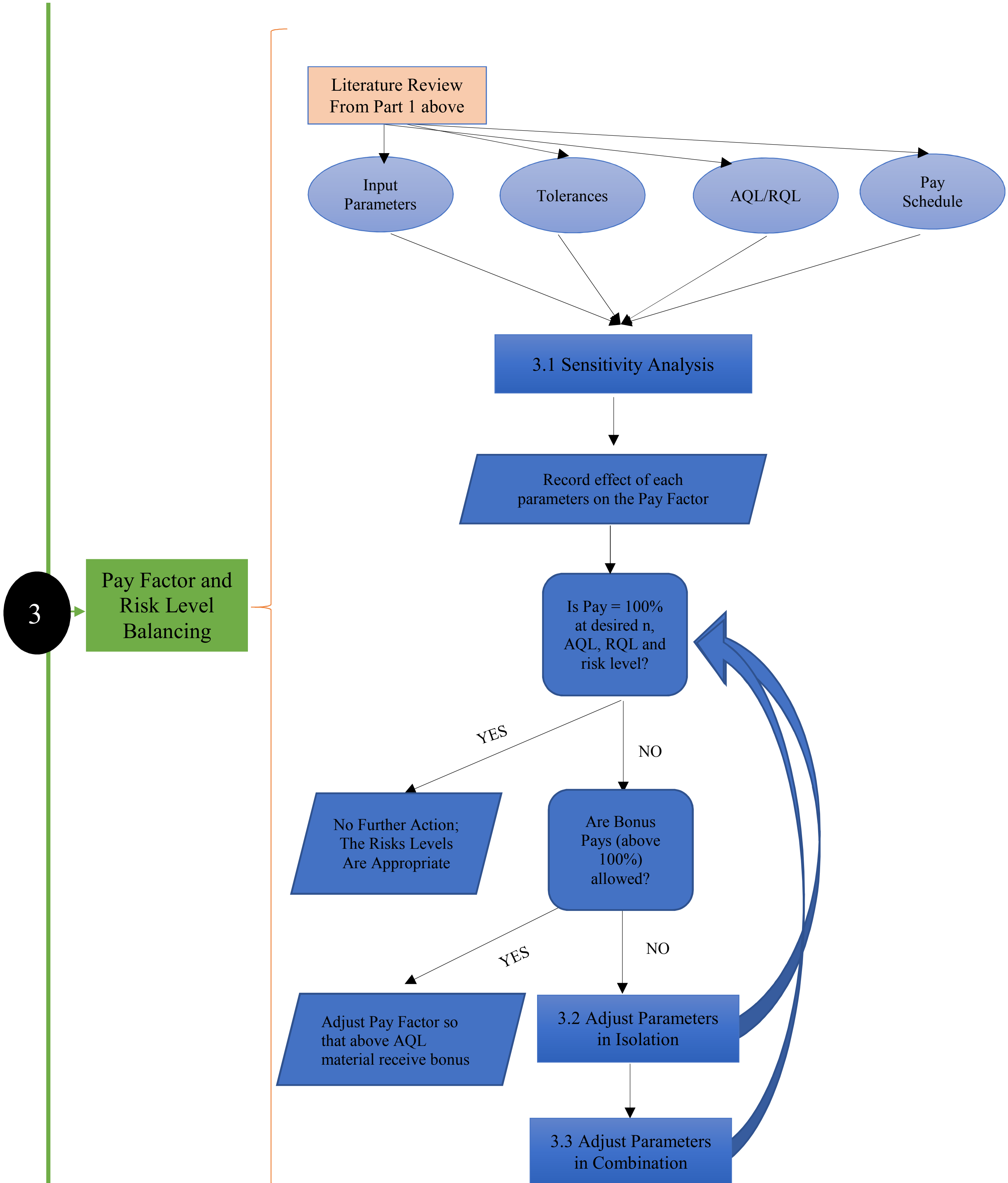


Figure 5.1 A Systematic Approach for Evaluating and Adjusting Agency and Contractor Risks for Highway Construction Material (cont.)

The steps of the suggested approach presented in Figure 5.1 are briefly described next:

1- Analyze the current status (Step1)

   a. Perform sensitivity analysis (Step 1.1) to assess the effects of each input variable on the material performance indicator.

   b. Build the OC curves (Step1.2) for quantifying alpha and beta errors given the current spec tolerances and acceptance levels – particularly focus on parameters that have the highest impact based on the sensitivity analysis results.

   c. Measure the effects of modifying the AQL and RQL (Step 1.3) on pay factor.

2- Simulation of production lots and risk analyses (Step 2)

   a. Determine the population characteristics for each material input variables and the performance quality indicator.

   b. Use the population characteristics to simulate production lots (Step 2.1).

   c. Based on the simulated lots assess Type I and Type II risks (Step 2.2) given the existing sample size, AQL and RQL (Step 2.2).

   d. Adjust the number of selected lots (n) and observe effects on risks. Assess if there is a reasonable sample size that results in desirable risk levels (Step 2.2).

   e. Adjust the AQL and RQL and observe the effect on risks. Identify if reasonable AQL and RQL produce the desirable risk levels (Step 2.2).

f. Adjust the tolerances to observe the effect on acceptance risks. Identify level of tolerances that provide the desired risks levels (i.e., as identified by AASHTO) (Step 2.2).

g. If the desired levels of risk are not achieved by modifying each of the above parameters (AQL, RQL, n, specification tolerances), proceed in modifying a combination of such variables until a reasonable level of risks are achieved (Step 2.3).

3- Analyze the current pay factor and make necessary adjustments

a. Perform sensitivity analysis on the pay factor by changing each material parameter by a reasonable range to determine the most prominent parameters (Step 3.1).

b. Perform sensitivity analysis on the risk levels by changing each material parameter by a reasonable range to determine the most prominent parameters (Step 3.1).

c. Adjust the pay factor equation so that at the chosen sample size, AQL and desired risk levels, material at the AQL receives 100% pay.

d. If achieving 100% pay factor for material at AQL is not possible with reasonable and achievable levels of inputs, consider adding incentive pays. It is important to review whether inventive pays are compliant with the applicable agency rules and regulation. If yes, adjust the pay factor equation should be adjusted so that pay factors reward material that achieve higher than AQL. This will allow for the average pay of material at AQL to reach 100% pay.

e. In most cases, a linearly decreasing pay factor equation is appropriate with pay factor dropping to zero at a level where quality of the material becomes unacceptable.

f. If the desired risk levels and pay are not achieved, adjust parameters in isolation or in combination to achieve the desired outcome (Steps 3.2 and 3.3).

5.3 Application of the methodology in HMA

This section presents the steps of the suggested methodology by using the case of HMA. The results and the analysis presented in the previous chapters are thus used in doing so. It is important to note that in previous chapters, any adjustment made to characteristics of material parameters or the specification parameters was based at varying one parameter at the time. In the analyses herein multiple parameters are adjusted concurrently (i.e., similar to a stepwise multivariate analysis).

1- Analyze the Current Status

As discussed in Chapter 3, the historic data that obtained from the literature and past studies pointed to a normal distribution for of all parameters that constitute the Dynamic Modulus (E*) and the predicted life (Y). The mean and standard deviation of each material parameter was also obtained and later used in the simulation steps.

Chapter 3 presented the summary results of the sensitivity analyses performed. It was concluded that E* is most sensitive to changes in P_{38}. Production tolerances for each of the material parameters were obtained from different states. Typical levels of AQL and RQL were also identified. Then, the Type I and Type II risks for E* were calculated and analyzed, as reported in Figure 5.1 and Table 5.1 below. It was concluded that, as expected, the OC curves approach a step function as the sample sizes increase which translates into the fact that higher sample sizes better represent the true population of the tested material.

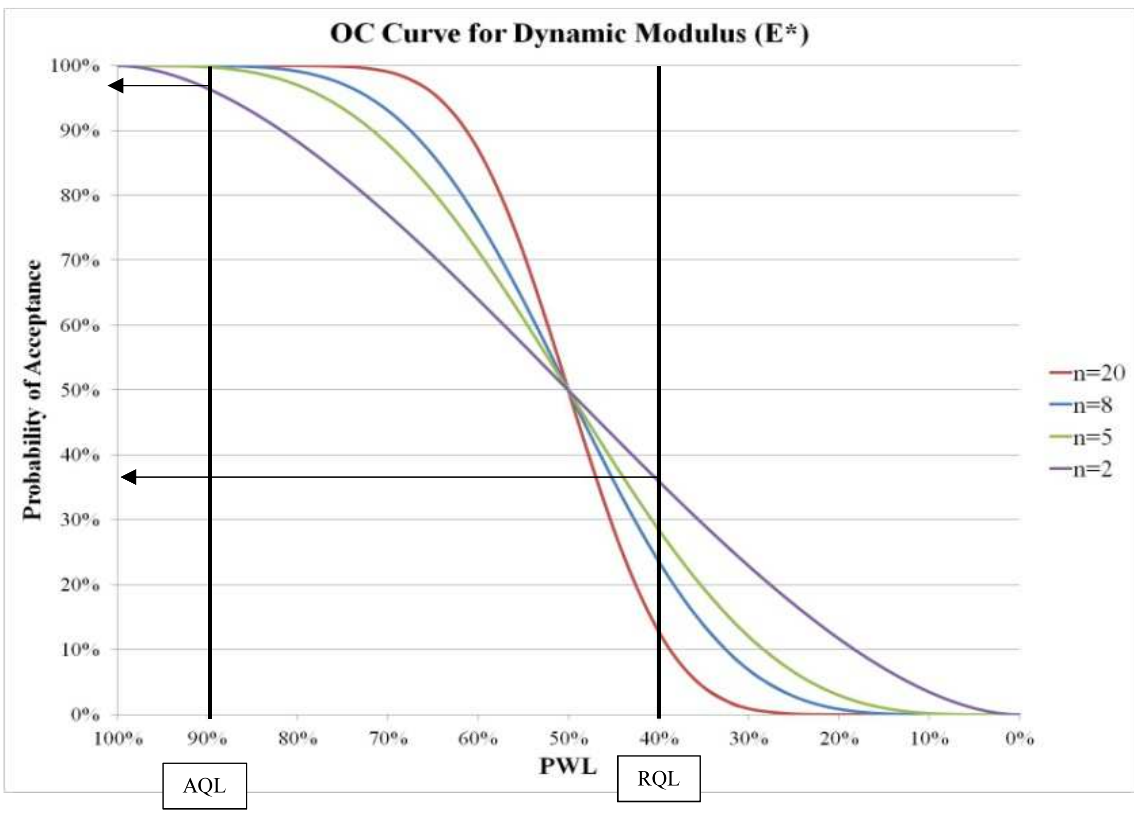


Figure 5.1 OC curves for dynamic modulus (E*)

Table 5.1 Comparison of risks for AQL at 80% and 90%

	AQL=80%, RQL=40%		AQL=90%, RQL=40%	
Sample size (n)	**Type I**	**Type II**	**Type I**	**Type II**
20	0%	13%	0%	13%
8	1%	23%	0%	23%
5	3%	28%	0%	28%
2	11%	36%	3%	36%

The sensitivity analysis was later performed on Type I, Type II risks and pay factor risk by adjusting the sample size and AQL. The results were summarized in tables 3.6 and 3.7 as well as figures 3.7 through 3.10 of Chapter 3. This allowed for discovering that the relationship between the determined quality levels (AQL and RQL) is not linear with the corresponding risk types (Type I and Type II). Furthermore, it was concluded that Type II risk may be reduced by either reducing the RQL or increasing the sample size.

2- Simulation Analysis Steps

a. As discussed previously, a normal distribution was assumed for the parameters that constitute E* (equation 3.1).

b. The mean and standard deviation for each material parameter was based on experimental results from the literature and past studies as discussed in Chapter 3.

c. Using a simulation software (e.g., Matlab, Excel etc.) simulate values of each parameter. The number of simulations should be enough so that the distribution of the simulated values resembles the assumed distribution in Step 2 above. In this study 500,000 simulated lots were used.

d. For each simulation run (i.e., one simulation of each parameter that ultimately forms the E*) calculate the final material parameter (in this case E*) and consecutively Y (i.e., corresponding life in years). Figure 5.2 indicates that Y follows a normal distribution which is the expected behavior given the underlying assumption was that each parameter and therefore Y is normally distributed.

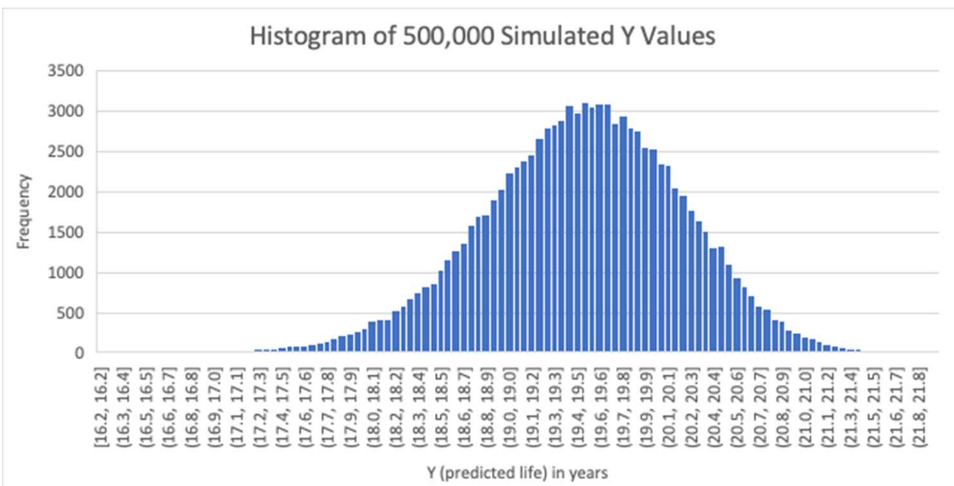


Figure 5.2 Distribution of 500,000 simulated Y (predicted life in years) values

3- Sample size, OC curves and identification of acceptance risks

Sample size directly affects the risk levels. Therefore, the effect of sample size (n) should be examined on both Type I and Type II risks in order to find a balance of risk that both the agency and the contractors serving the agency find appropriate. This was an attempt to find the risk levels suggested by AASHTO R-9. In order to find the risk levels at each sample size, it is necessary to build Operating Characteristic (OC) curves. Chapter 3 provided the detailed results and analysis of OC curves and risk levels.

4- Performance prediction (ΔY) and Pay Factor Analysis (Expected Pay)

As mentioned in the simulation steps above, for each simulation run, the performance parameter is predicted and then compared to its relative benchmark. In this case, the performance parameter (predicted service life or Y) was compared to the design life (Y_c) to calculate ΔY. Furthermore, by calculating ΔY, the respective pay factor can also be calculated. This allows for relating the relative performance to expected pay. This was discussed and analyzed in sections 3.3. and 4.8.

5- Final Balancing and Results

In the final step, the above-mentioned analyses are considered in order to balance the risk levels and corresponding pay factors. This final step is the objective of this section and not fully discussed and implemented in the previous analysis.

In this final step it is critical to have a good knowledge of the achievable levels of product quality by the industry in order to identify feasible strategies for balancing risks and PF. If the AASHTO required risk levels are achieved by implementing such adjustments, then the goal is achieved. However, in some cases, as discussed below, this is not always achievable which may require adjusting the pay factor schedule in the specification in order to achieve the desired balance between risks and pay.

5.4 Pay factor and risk levels

A pay factor model was recommended in the NCHRP 704 national study. This was considered as a starting step in estimating the implied PF difference between the average pay per lot (e.g., simulated lots with n=3, n=6, etc.) and the population PF (n=1). Table 5.1 summarizes the results and indicates how the current pay factor model results in consistently lower payments of lots (i.e., with n=3, 6, etc.) compared to the population pay.

Table 5.1 Difference between population pay factor and pay factor of lots with different sample sizes

Sample Size (n)	Alpha	Beta	Pay Difference[1]
3	1.30%	33.0%	-0.33%
6	0.10%	26.7%	-0.33%
8	0.01%	23.7%	-0.32%
10	0.00%	21.2%	-0.32%
20	0.00%	12.9%	-0.32%
40	0.00%	5.5%	-0.31%

Note: Pay difference is defined as the difference between average of the payment of all simulated lots (i.e., n=3,6, etc.) and the payment of the population (n=1) estimated with 500,000 simulated lots.

The first observation from Table 5.1, is that the desired risk levels for alpha and beta are achieved at different sample sizes (Alpha is ~1% at n=3 and Beta is ~5% at n=40).

It is also important to note that the observed trend in Table 5.1 (i.e., decrease in pay difference as sample size increases, even though such differences are minimal) is the correct and expected trend. In this case, since almost all the simulated lots have a pay factor of 100% this produced the small differences in PF observed in Table 5.1 results. The main reason for this is the granular pay factor used which is a clear indication that the pay factor needs to be adjusted so that it reflects the effect of sample size change (and consequently the alpha and beta). An ideal pay factor would be built in a way that above a certain performance threshold, the pay factor increases linearly. Furthermore, when both risks increase the pay factor difference of the sample size and population should increase as well.

A possible adjustment to the NCHRP 704 pay factor model (Figure 5.3), is to change the stepwise shape of the pay factor to a more linearly increasing function. This adjustment is illustrated in Figures 5.3 and 5.4.

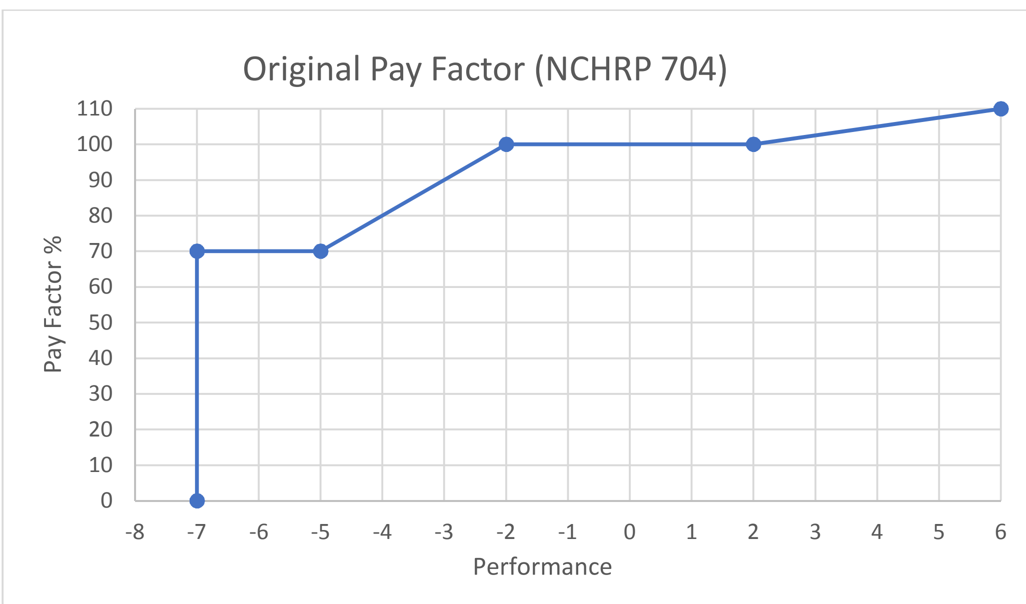


Figure 5.3 Original pay factor (NCHRP 704)

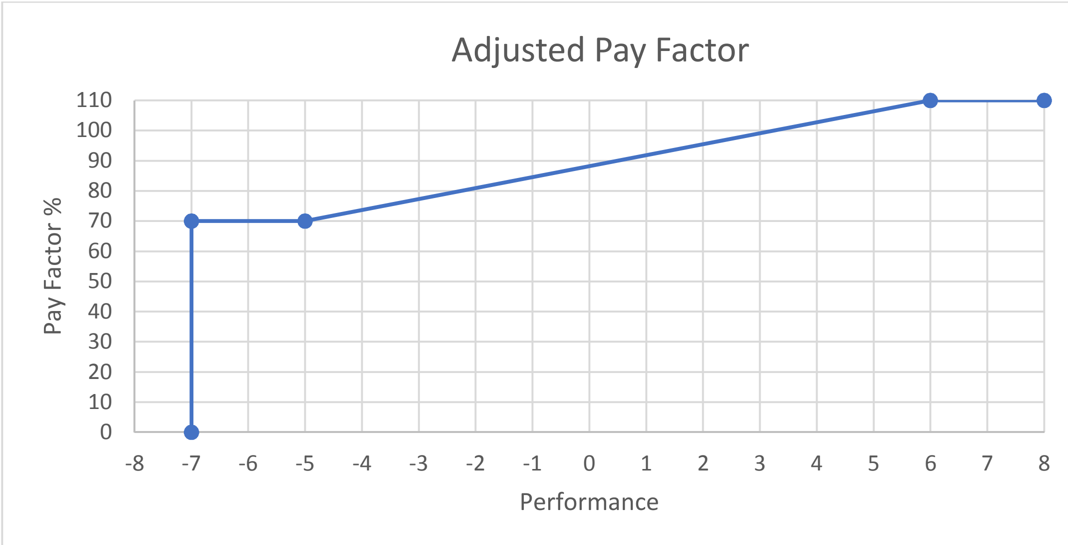


Figure 5.4 Adjusted pay factor

The adjusted pay factor results in more material pay differences as shown in Table 5.2 below. However, the change in pay difference as the sample size increases is still negligible, which suggests that further and more drastic adjustments to the pay factor are needed than the one suggested in Figure 5.4. Ultimately, the goal is that the suggested pay difference at difference sample sizes achieves a balanced risk between the producer and the agency and incentivizes appropriate quality material without significantly increasing the sampling size which has implications in QC cost for the agency.

Table 5.2 Difference in population PF and pay factor at different sample sizes with Original Pay Factor and Adjusted Pay Factor

Sample Size (n)	Alpha	Beta	Pay Difference Original Pay Factor	Pay Difference Adjusted Pay Factor
3	1.30%	33.0%	-0.33%	2.55%
6	0.10%	26.7%	-0.33%	2.55%
8	0.01%	23.7%	-0.32%	2.60%
10	0.00%	21.2%	-0.32%	2.61%
20	0.00%	12.9%	-0.32%	2.42%
40	0.00%	5.5%	-0.31%	2.47%

This analysis indicates that adjustments to the pay factor equation in isolation are not enough to provide meaningful changes in pay based on sample sizes. Therefore, adjustments to other levers (i.e., quality parameters) are necessary. In the follow-up analysis adjustments to the following parameters were explored:

1- Upper and lower limit tolerances which in turn result in adjustments to Acceptable Quality Level (AQL) and Rejectable Quality Level (RQL).

2- Potential changes in mean and variability of production quality.

As examined in Chapter 4 section 4.7, changing only the acceptance tolerances for each material property in order to achieve the AASHTO recommended risk levels indicated that in some cases a reduction of more than 10 times is needed (Table 4.7) , which most likely represents a non-achievable level of production uniformity by many production plants. Therefore, in addition to having tighter specification tolerances, having production plants that are capable of producing with lower standard deviation must also be considered.

The results of Table 5.3 that were initially presented in Chapter 4 indicated the effect of keeping the standard deviations fixed when solving for new tolerances. If the producers were capable of improving production uniformity by 10% (i.e., reducing the standard deviation of the population by 10%), the new tolerances could be adjusted to those Table 5.4.

Table 5.3 New specification tolerances for individual parameters achieved while assuming no improvement to the production's standard deviation

Property	Current Tolerance	**New Tolerance**
P200	±2%	**±0.21%**
P4	±5%	**±3.64%**
Va	±0.5%	**±0.05%**
Vbeff	±0.5%	**±0.01%**
P38	±6.0%	**±1.77%**
P34	UL 100 LL 93	**±0.00%**

Table 5.4 Current tolerances versus newly suggested tolerance to meet the desired risk levels at a reduced production variability

Property	Current Tolerance	New Tolerance*
P200	±2%	±0.25%
P4	±5%	±4.41%
Va	±0.5%	±0.06%
Vbeff	±0.5%	±0.01%
P38	±6.0%	±2.14%
P34	UL 100 LL 93	±0.00%

Note: *Required tolerances to meet (α= 1% and β = 5%) when production variability is reduced by 10%

Although the new tolerances in Table 5.4 (based on 10% improvement in production variability) are not as tight as those in Table 5.3, they are still significantly reduced compared to the currently implemented tolerances, and most likely still practically not achievable by the industry. This concludes that although improvements to production variation can slightly alleviate the need for significantly tighter tolerances, it is not enough in isolation.

Given these findings and those presented in Chapter 4, it can be concluded that combining adjustments in both tolerances (which represents production quality) and risk levels (alpha and beta) might be a reasonable multivariate solution.

In order to achieve this, a 10% improvement in production variability is assumed as achievable (i.e., tightening tolerances by 10%) combined with a higher level or risks. Considering the AASHTO recommended risks levels, Table 5.5, this implies moving from the "major" to "minor" tier. In other words, the recommended alpha will be 0.5%

while recommended beta will be 10%. It is important to note that a 10% improvement for the lower end producers may prove to be challenging which may result in supply challenges across the region and should be evaluated on a case-by-case basis.

Table 5.5 Recommended risk levels by AASHTO R-9 for different project criticality levels

Criticality[1]	Recommended α	Recommended β
Critical	0.050	0.005
Major	0.010	0.050
Minor	0.005	0.100
Contractual	0.001	0.200

[1]Critical: when the requirement is essential to preservation of life.
Major: when the requirement is necessary for the prevention of substantial financial loss.
Minor: when the requirement does not materially affect performance.
Contractual: when the requirement is established only to provide uniform standards for bidding.

By repeating the process and calculating the tolerances based on the abovementioned alpha and beta, the following new tolerances are obtained.

Table 5.6 New tolerances for each parameter for risk levels of "minor" criticality

Property	Current Tolerance	New Tolerance*
P200	±2%	±0.27%
P4	±5%	±4.88%
Va	±0.5%	±0.07%
Vbeff	±0.5%	±0.02%
P38	±6.0%	±2.37%
P34	UL 100 LL 93	±0.00%

*Results for alpha 0.5% and beta 10%

Similarly, although there is slight improvement in the new tolerances, the changes compared to the current tolerances are too significant to be implemented by the asphalt producers.

As discussed above, it is clear that even changing multi factors simultaneously, the new tolerances are generally too tight to reasonably expect a producer to achieve them. Therefore, it is recommended to focus on the tolerances and risk levels of the Dynamic Modulus rather than the individual components/properties. The next steps look into finding the appropriate tolerance and risk levels for the Dynamic Modulus.

Initially, the abovementioned simulated lots have been used to calculate the Dynamic Modulus of each lot, which have been identified as the "population". Furthermore, AASHTO PP62 (*Standard Practice for Developing Dynamic Modulus Master Curves for Hot Mix Asphalt*) suggests a ±13% tolerance level. As discussed in Chapter 4, based on the asphalt samples data obtained from Appendix E of the NCHRP 704 study report, using the ±13% tolerance results in a PWL of 88.6%. Thus, this population it is impossible to achieve an AQL of 90% for calculate the corresponding risk. Therefore, the benchmark tolerance for E* is increased to be ±15% in order to accommodate for this. This resulted in the following risk levels at different sample sizes.

Table 5.7 Alpha and Beta risk levels at different sample sizes for E* with ±15% tolerance (AQL =90% and RQL=40%)

Sample Size	20	10	8	6	4	2
Alpha (Type I)	0.000%	0.001%	0.007%	0.049%	0.355%	2.907%
Beta (Type II)	12.9%	21.2%	23.7%	26.8%	30.6%	36.0%

The corresponding PF using the NCHRP704 pay factor model, presented in Figure 3.6, provided the results presented in Table 5.8.

Table 5.8 Pay factors for E* at different sample sizes and risk levels

Sample Size	20	10	8	6	2
Alpha (Type I)	0.00%	0.01%	0.07%	0.49%	2.91%
Beta (Type II)	12.9%	21.2%	23.7%	26.8%	36.0%
Pay Factor	100%	100%	100%	100%	100%

This illustrates that the 15% tolerance and possibly the AQL need to be adjusted in order to better balance risk levels (alpha and beta) with pay factor. Extensive analysis of such adjustments was examined in Tables 3.6 and 3.7 of Chapter 3. However, as recommended above, such adjustments should reflect gradual changes to PFs. Reducing AQL from 90% to 85% and RQL from 40% to 30%, is a potentially acceptable adjustment for a highway agency in order to control risk levels. It is important to note that although RQL at 30% level is not widely used by several state agencies, it still falls in the acceptable range as reported by WSDOT in the study on "*A Quantification and Evaluation of WSDOT's Hot Mix Asphalt Concrete Statistical*

Acceptance Specification (2001). On the other hand, AQL of 85% has been identified as an acceptable level by Federal Highway Administration in a study examining "Optimal Acceptance Standards for Statistical Construction Specifications" (*Publication Number: FHWA-RD-02-095).* As discussed earlier, a 10% improvement in production quality represents an achievable level by asphalt producers. Combining the effect of these three quality parameters (AQL = 80%, RQL = 30%, and reducing the tolerance by 10%), the results of Table 5.9 were obtained:

Table 5.9 Risk levels and pay factors at different sample sizes of E* - RQL=30%, AQL=85%

Sample Size	20	10	8	6	2
Alpha (Type I)	0.00%	0.04%	0.15%	0.50%	6.85%
Beta (Type II)	1%	5%	7%	10%	23%
Pay Factor	100%	100%	100%	100%	95%

As illustrated in Table 5.9, with a sample size of n=6, the desired risk levels (alpha = 0.5% and beta = 10%) and a pay factor of 100% can be achieved by reducing the AQL from 90% to 85%, RQL from 40% to 30% and improving production quality by 10%. Still a 10% production quality improvement may not be easily achieved by all contractors. Furthermore, as mentioned reducing RQL to 30% might not be desirable by all state DOTs. Therefore, state agencies are encouraged to consider such adjustments on a case-by-case basis.

In this example, there is no need to adjust the pay factor (e.g., to add a bonus provision) suggested by NCHRP 704 as the pay factor at AQL is already 100%. The only question that needs to be answered, also on a case-by-case basis, is whether the required sample size to achieve the desired results (n=6 in this case) is cost effective. In this analysis, most states are already operating by taking 5 to 6 samples which makes the proposed solution acceptable.

Since state agencies identify the sample size and acceptable/rejectable levels, it is strongly recommended that they consider adjusting their pay factors to incentivize lower risk levels for the agency and the contractors. As a reminder, in the example above, the desired risk levels (alpha = 0.5% and beta =10.0%) are achieved when 6 samples are taken. Lower risk levels require higher number of samples to assess the lot quality, which result in higher QC cost. However, in the long run, when risk levels are lower than the target levels, the state agency is further assured that the product in hand is closer to the desired quality. In order to accommodate for such adjustment, a Risk-Based Multiplier (RBM) must be assigned to the pay factor that incentivizes lower risk levels. It is most appropriate to choose the Type II (Beta) as risk level that the pay factor gets adjusted based on. This is due to:

1- Agencies accept a higher level of risk under the AASHTO R-9 guidelines (Table 5.5), and,
2- Agencies are in charge of setting the acceptance criteria, although in collaboration with the contractors.

In Table 5.10 the original NCHRP 704 pay factor is shown followed by the suggested RBM adjustment. Using the NCHRP 704 pay factor as the base model makes this approach more feasible for state agencies that are already using such pay factor. As shown below, the thresholds of the RBM are chosen at the *Target Beta* and *2xTarget Beta*. Although these thresholds can be adjusted based on the material and agency requirements under study, the AASHTO R-9 recommended risk levels suggest that when agency risk (beta) increases by 2x, the criticality category of the project changes (e.g., from "Major" to "Minor). Therefore, the 2x threshold is an appropriate one.

Table 5.10 NCHRP 704 Pay Factor and recommended risk-adjusted pay factor

NCHRP 704 Pay Factor	Recommended Risk-Adjusted Pay Factor
$\Delta Y < -7 \rightarrow PF = 0$ $-7 \leq \Delta Y \leq -5 \rightarrow PF = 70\%$ $-5 < \Delta Y < -2 \rightarrow PF = 0.1*\Delta Y+1.2$ $-2 \leq \Delta Y \leq -2 \rightarrow PF = 100\%$ $2 < \Delta Y < 6 \rightarrow PF = 0.025*\Delta Y+0.95$ $\Delta Y \geq 6 \rightarrow PF = 110\%$	$\Delta Y < -7 \rightarrow PF = 0$ $-7 \leq \Delta Y \leq -5 \rightarrow PF = 70\% * RBM$ $-5 < \Delta Y < -2 \rightarrow PF = (0.1*\Delta Y+1.2)*RBM$ $-2 \leq \Delta Y \leq -2 \rightarrow PF = 100\% * RBM$ $2 < \Delta Y < 6 \rightarrow PF = (0.025*\Delta Y+0.95)*RBM$ $\Delta Y \geq 6 \rightarrow PF = 110\%*RBM$ Where RBM is: Beta ≥ Target Beta → RBM = 1.00 0.5*Target Beta < Beta ≤ Target Beta → RBM = - 2(Beta%) + 1.20 Beta < 0.5xTarget Beta → RBM = 1.10

Figure 5.5.a and 5.5.b depict the two parts of the Risk-Adjust Pay Factor (Table 5.10). The first graph, Figure 5.5a, represents the performance-based pay factor (i.e., what is widely used today). The second graph, Figure 5.5b illustrates the Risk-Adjusted Pay Factor which is recommended as the new (risk based) dimension to the pay factor.

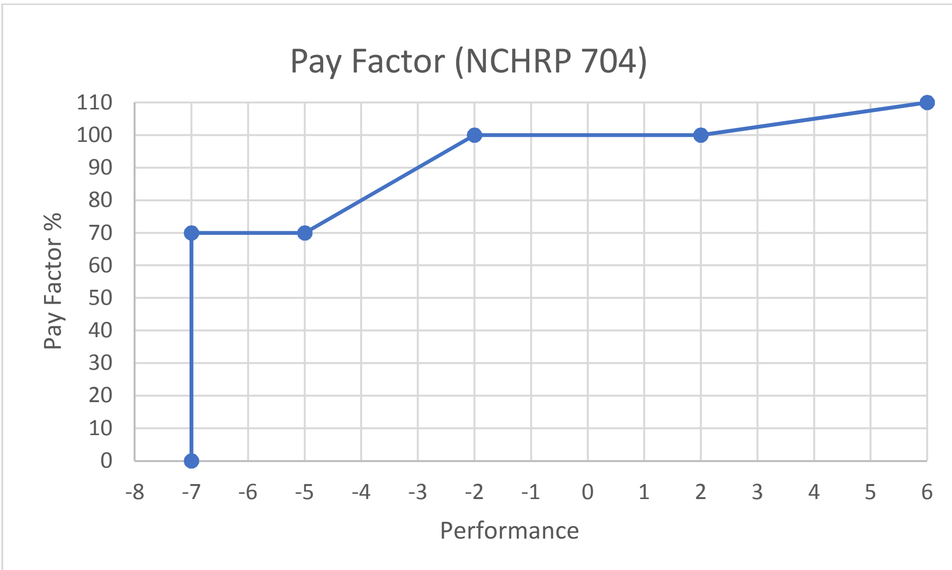


Figure 5.5.a Performance-based part of the pay factor

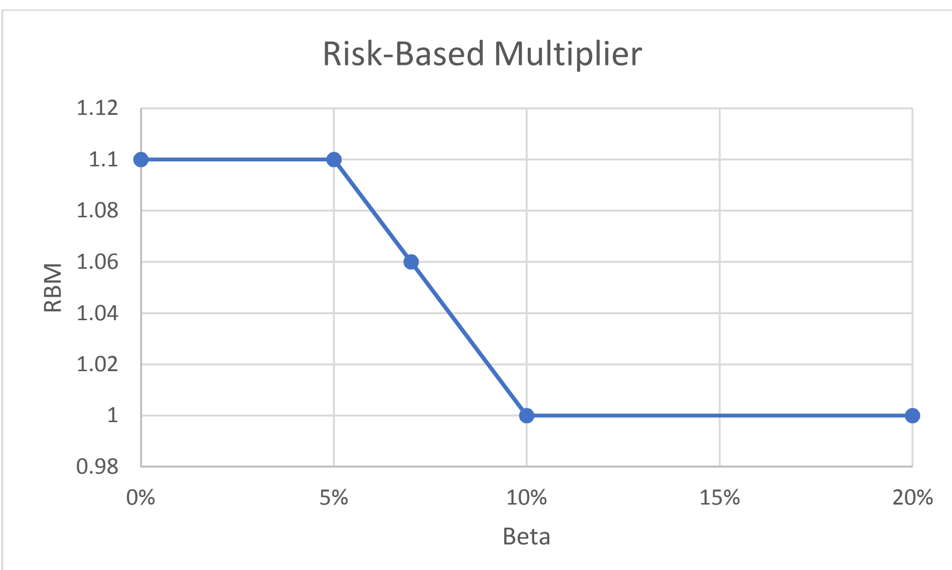


Figure 5.5.b Risk-Based Multiplier for the pay factor illustrated in Figure 5.5.a

As an example, and in order to illustrate the effects of the suggested Risk-Adjust Pay Factor, the simulated Dynamic Modulus values from the analysis of this research were used. Table 5.11 presents the results. As it can be seen, the RBM adjusts the original pay factor to result in higher pay factors when Beta decreases. In other words, as intended, lower risk levels are incentivized with higher pay.

Table 5.11 Risk-based pay factor at different sample sizes of E*

Sample Size	20	10	8	6	4	2
Alpha (Type I)	0.00%	0.04%	0.15%	0.50%	4.62%	6.85%
Beta (Type II)	1%	5%	7%	10%	15%	23%
Original Pay Factor	100%	100%	100%	100%	97%	95%
RBM	1.10	1.10	1.06	1.00	1.00	1.00
Risk-Adjusted Pay Factor	110%	110%	106%	100%	97%	95%

The results of Figures 5.6 and 5.7 further generalize the validity of the suggested pay factor (Table 5.10). Based on further simulation analysis, new lots of E* were simulated and different sample sizes were taken (i.e., varying the sample size n) while all other parameters remained the same. The results are depicted in Figure 5.6 where the Risk Adjusted Pay Factor versus the lot sample size was examined. As expected, and by design, larger sample sizes are associated with larger pay factors. This is due to the fact that at lower sample sizes, the beta risk increases (as depicted in Figure 5.1) which results in a lower pay factor and RBM.

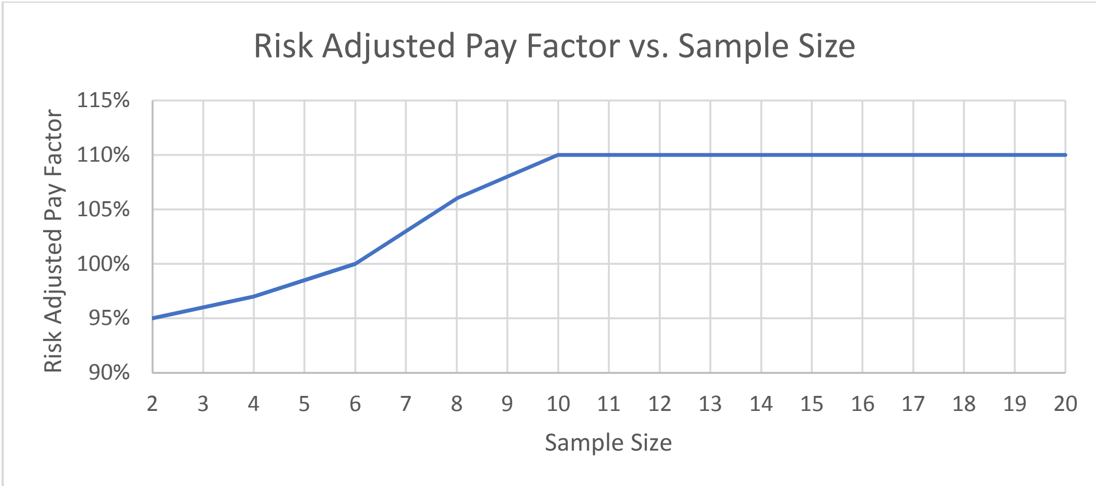


Figure 5.6 Risk-Adjusted Pay Factor vs. Sample Size (n)

In Figure 5.7 the effect of beta on the Risk Adjusted Pay Factor is illustrated. As discussed earlier, the intention of the suggested Risk-Adjusted Pay Factor was to incentivize lower levels of risk which is the behavior that is also observed in Figure 5.7.

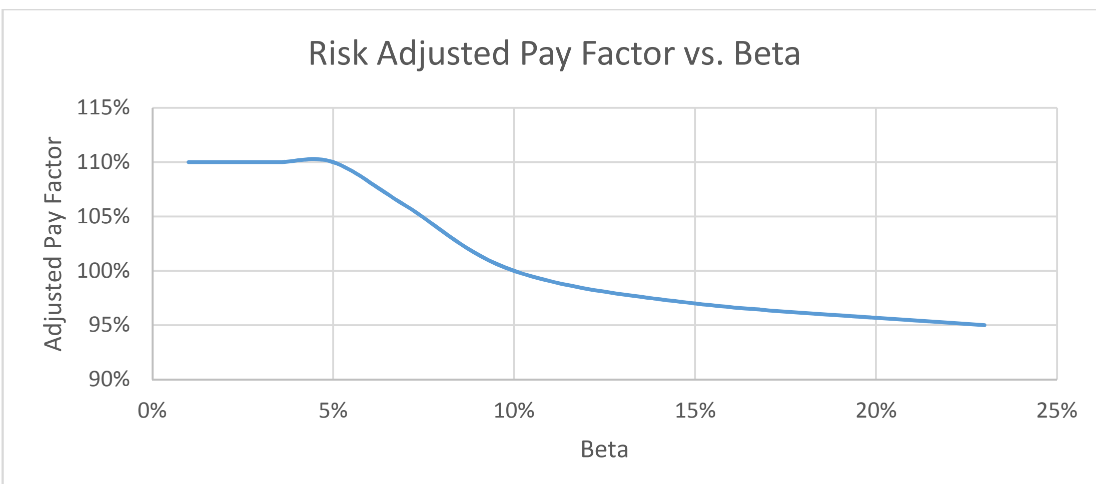


Figure 5.7 Risk-Adjusted Pay Factor vs. Beta

Figure 5.8 presents the relationship between the Beta risk and sample size (n). This relationship was thoroughly analyzed in figures 3.7 thought 3.10 and as expected larger sample sizes are associated with lower risks. This is also expected as larger sample sizes result in the samples becoming closer and closer to the population characteristic, and thus as a result reducing the risk levels.

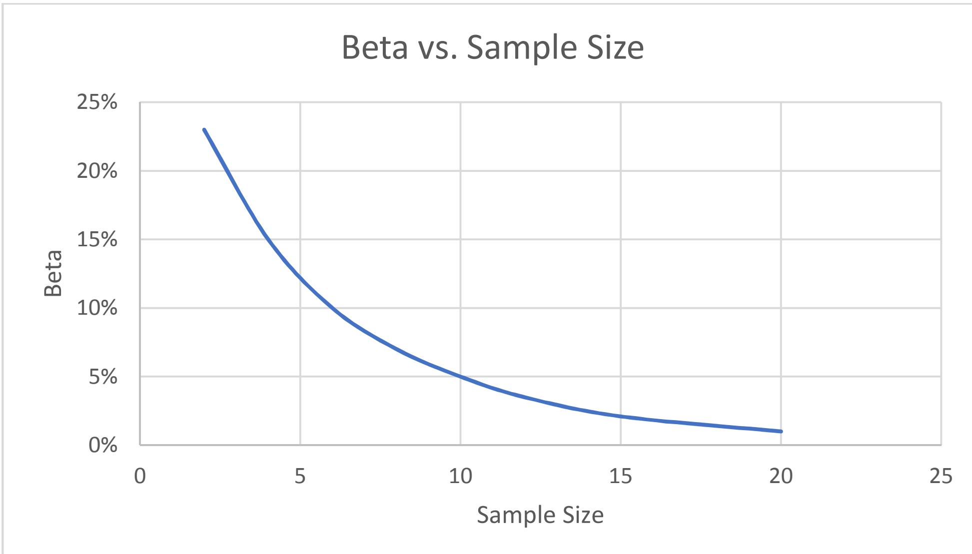


Figure 5.8 Risk-Adjusted Pay Factor vs. Beta

5.5 Summary and recommendations

In summary, in Chapter 5 a robust and novel process was laid out in order to achieve the following for HMA, and eventually transferable to similar construction materials:

1- Relate acceptance risks to pay factors
2- Examine effects of quality (at acceptance levels) on performance
3- Relate performance to pay schedules
4- Identify different strategies (such as adjusting tolerances and/or pay factors) to balance acceptance risks & pay factors
5- Adjust the pay factors so that lower risk levels are achieved and incentivized

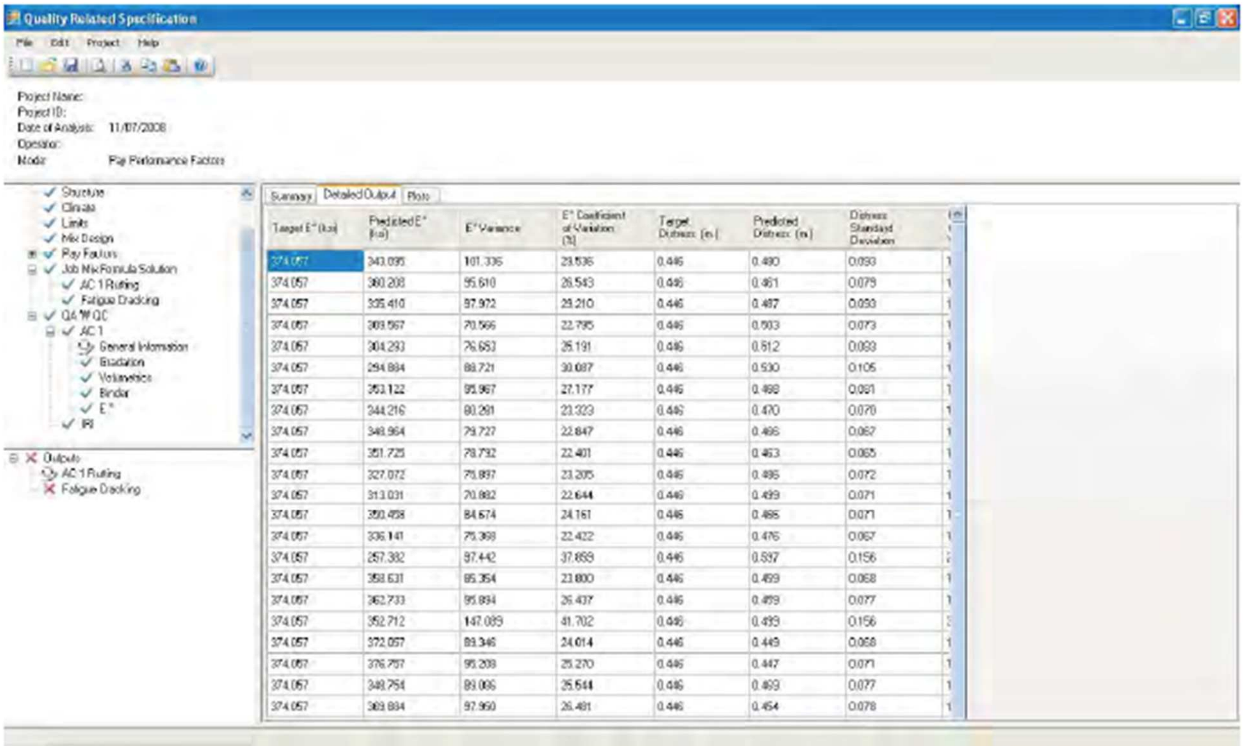
The process was applied to simulated HMA data and it was observed that adjusting variables in isolation does not lead to the desired balance between risk levels and pay factors. As a result, a step-by-step multivariate analysis was undertaken where both acceptance criteria (AQL, RQL and tolerance) and production quality was adjusted in order to achieve the desired balance between agency and contractor risk levels. It is important to note that while this multivariate analysis was performed, the practicality of the suggested changes (for example reducing production variability) often depends on the achievable levels of production quality by the industry. Furthermore, in order to incentivize for lower levels of risk, a new type of a pay factor was introduced which implements a risk-adjusted factor on top of an existing pay factor schedule.

This study can be further expanded by considering applying the process to other highway construction material and structures (e.g., aggregate base/subbase, concrete mixtures, asphalt and concrete pavements). The suggested approach can be customized to consider alternative acceptance plans, alternative production population distributions, multi-criteria quality parameters (i.e., such as smoothness thickness, strength), and so on. Furthermore, converting this methodology to a readily available tool can prove to be very useful for state agencies that may not have the expertise to perform such analysis inhouse.

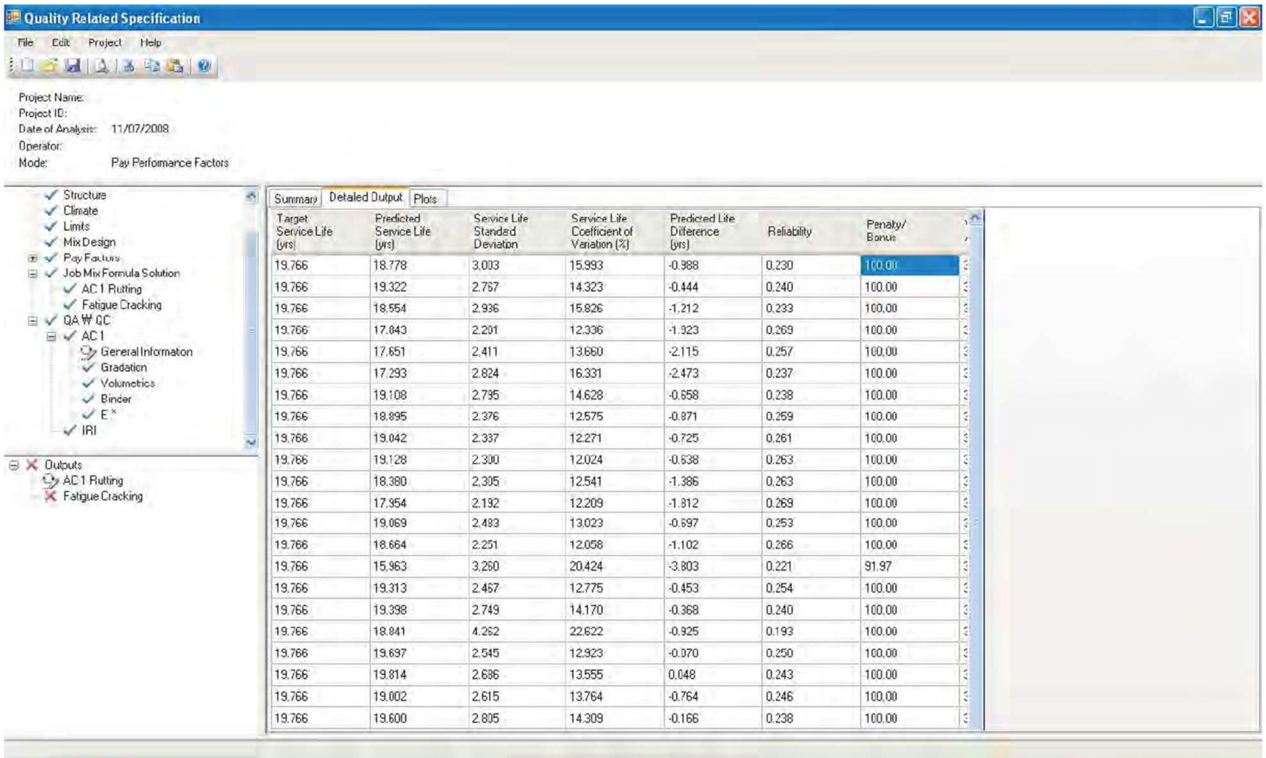
*** THIS PAGE IS INTENTIONALLY LEFT BLANK ***

Appendix

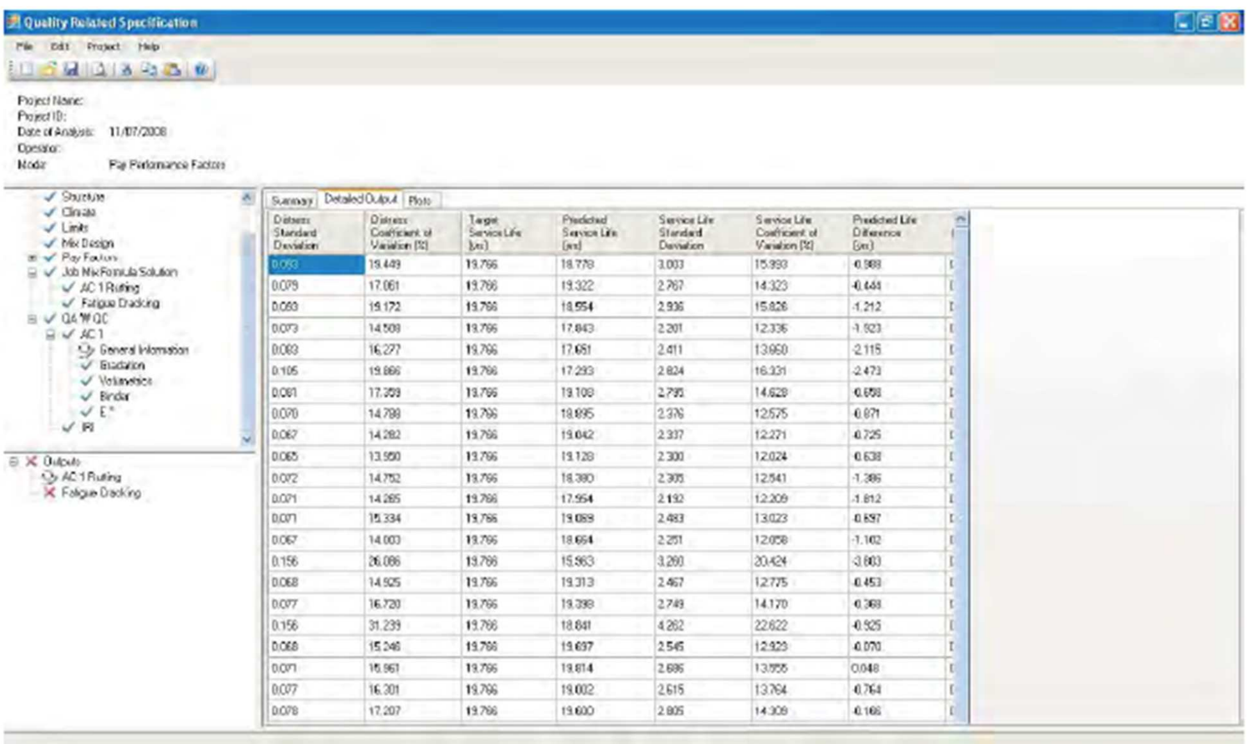
A.1 NCHRP 704 Study Data



Target E* (ksi)	Predicted E* (ksi)	E* Variance	E* Coefficient of Variation (%)	Target Distress (in)	Predicted Distress (in)	Distress Standard Deviation
374.057	343.095	101.336	29.536	0.446	0.490	0.093
374.057	360.208	95.610	26.543	0.446	0.461	0.079
374.057	335.410	97.972	29.210	0.446	0.487	0.090
374.057	309.567	70.566	22.795	0.446	0.503	0.073
374.057	304.293	76.653	25.191	0.446	0.512	0.093
374.057	294.884	88.721	30.087	0.446	0.530	0.105
374.057	353.122	95.967	27.177	0.446	0.468	0.081
374.057	344.216	80.281	23.323	0.446	0.470	0.070
374.057	348.964	79.727	22.847	0.446	0.466	0.067
374.057	351.725	78.792	22.401	0.446	0.463	0.065
374.057	327.072	75.897	23.205	0.446	0.495	0.072
374.057	313.031	70.882	22.644	0.446	0.499	0.071
374.057	350.458	84.674	24.161	0.446	0.465	0.071
374.057	336.141	75.368	22.422	0.446	0.476	0.067
374.057	257.382	97.442	37.859	0.446	0.597	0.156
374.057	358.631	85.354	23.800	0.446	0.459	0.068
374.057	362.733	95.894	26.437	0.446	0.459	0.077
374.057	352.712	147.089	41.702	0.446	0.499	0.156
374.057	372.057	89.346	24.014	0.446	0.449	0.068
374.057	376.757	95.208	25.270	0.446	0.447	0.071
374.057	348.754	89.086	25.544	0.446	0.469	0.077
374.057	369.884	97.960	26.481	0.446	0.454	0.078



Target Service Life (yrs)	Predicted Service Life (yrs)	Service Life Standard Deviation	Service Life Coefficient of Variation (%)	Predicted Life Difference (yrs)	Reliability	Penalty/ Bonus
19.766	18.778	3.003	15.993	-0.988	0.230	100.00
19.766	19.322	2.767	14.323	-0.444	0.240	100.00
19.766	18.554	2.936	15.826	-1.212	0.233	100.00
19.766	17.843	2.201	12.336	-1.923	0.269	100.00
19.766	17.651	2.411	13.660	-2.115	0.257	100.00
19.766	17.293	2.824	16.331	-2.473	0.237	100.00
19.766	19.108	2.795	14.628	-0.658	0.238	100.00
19.766	18.895	2.376	12.575	-0.871	0.259	100.00
19.766	19.042	2.337	12.271	-0.725	0.261	100.00
19.766	19.128	2.300	12.024	-0.638	0.263	100.00
19.766	18.380	2.305	12.541	-1.386	0.263	100.00
19.766	17.954	2.192	12.209	-1.812	0.269	100.00
19.766	19.069	2.483	13.023	-0.697	0.253	100.00
19.766	18.664	2.251	12.058	-1.102	0.266	100.00
19.766	15.963	3.260	20.424	-3.803	0.221	91.97
19.766	19.313	2.467	12.775	-0.453	0.254	100.00
19.766	19.398	2.749	14.170	-0.368	0.240	100.00
19.766	18.841	4.262	22.622	-0.925	0.193	100.00
19.766	19.697	2.545	12.923	-0.070	0.250	100.00
19.766	19.814	2.686	13.555	0.048	0.243	100.00
19.766	19.002	2.615	13.764	-0.764	0.246	100.00
19.766	19.600	2.805	14.309	-0.166	0.238	100.00



Distress Standard Deviation	Distress Coefficient of Variation (%)	Target Service Life (yrs)	Predicted Service Life (yrs)	Service Life Standard Deviation	Service Life Coefficient of Variation (%)	Predicted Life Difference (yrs)
0.093	19.449	19.766	18.778	3.003	15.993	-0.988
0.079	17.061	19.766	19.322	2.767	14.323	-0.444
0.083	19.172	19.766	18.554	2.936	15.826	-1.212
0.073	14.508	19.766	17.843	2.201	12.336	-1.923
0.083	16.277	19.766	17.651	2.411	13.660	-2.115
0.105	19.866	19.766	17.293	2.824	16.331	-2.473
0.081	17.359	19.766	19.108	2.795	14.628	-0.658
0.070	14.788	19.766	18.895	2.376	12.575	-0.871
0.067	14.282	19.766	19.042	2.337	12.271	-0.725
0.065	13.950	19.766	19.128	2.300	12.024	-0.638
0.072	14.752	19.766	18.380	2.305	12.541	-1.386
0.071	14.285	19.766	17.954	2.192	12.209	-1.812
0.071	15.334	19.766	19.069	2.483	13.023	-0.697
0.067	14.003	19.766	18.664	2.251	12.058	-1.102
0.156	26.086	19.766	15.963	3.260	20.424	-3.803
0.068	14.925	19.766	19.313	2.467	12.775	-0.453
0.077	16.720	19.766	19.398	2.749	14.170	-0.368
0.156	31.239	19.766	18.841	4.262	22.622	-0.925
0.068	15.246	19.766	19.697	2.545	12.923	-0.070
0.071	15.961	19.766	19.814	2.686	13.555	0.048
0.077	16.301	19.766	19.002	2.615	13.764	-0.764
0.078	17.207	19.766	19.600	2.805	14.309	-0.166

A.2 Simulation Tool

The simulation tool for this study was developed in Excel. Below is an example screenshot illustrating a few simulation runs for each parameter based on the inputted population characteristics

6					Inputs							
7		P200	P4	Va	Vbeff	P38	P34	f	Viscosity	# of Samples	AQL	RQL
8	Mean	5.258333333	42.05	7.533333333	5.107083333	89.1375	100	57.12	0.400917343	6	0.9	0.4
9	Std. Dev	0.483835946	1.958528359	0.23570226	0.113998508	0.68279641	0.001	NA	NA			
10	Tolerance	±2%	±5%	±0.5%	±0.5%	±6.0%	UL 100 LL 93					
11	UL	6.01	47.05	8.03	5.61	95.14	100.00					
12	LL	4.51	37.05	7.03	4.61	83.14	93.00					
13	PWL of Pop	87.9%	98.9%	96.6%	100.0%	100.0%	100.0%					
14	Mean at AQL	5.55	38.91	7.81	4.72	93.84	100.00					
15	PWL @ AQL	81.3%	82.9%	82.8%	82.9%	97.1%	82.9%					
16	PoA @AQL	99.0%	99.0%	99.0%	99.0%	100.0%	99.0%					
17	Type I / α / Contractor Risk	1.0000000058%	0.9999999167%	0.9999999773%	1.0000000814%	0.0001638118%	1.0000000118%					
18	Mean at RQL	4.18	35.73	8.19	4.53	96.05	100.00					
19	PWL @ RQL	25.1%	25.1%	25.1%	25.1%	9.0%	25.1%					
20	PoA @RQL	5.0%	5.0%	5.0%	5.0%	0.1%	5.0%					
21	Type II / β / Agency Risk	4.99999%	4.99999%	4.99999%	4.99998%	0.05015%	5.00001%					
22					Simulation of population of E*							
23	P200	P4	Va	Vbeff	P38	P34	f	n	E*			
24	5.29	38.81	7.66	5.08	88.46	100.00	57.12	0.40	0.38315			
25	4.15	42.79	7.31	4.99	88.40	100.00	57.12	0.40	0.36754			
26	5.10	43.77	7.36	5.02	89.48	100.00	57.12	0.40	0.35235			
27	5.62	39.35	7.68	4.97	89.43	100.00	57.12	0.40	0.36916			
28	5.43	43.57	7.58	5.18	88.72	100.00	57.12	0.40	0.35805			
29	5.58	43.04	7.14	4.98	89.62	100.00	57.12	0.40	0.36616			
30	4.53	40.32	7.09	5.15	88.29	100.00	57.12	0.40	0.38645			
31	5.12	42.37	7.95	5.06	89.06	100.00	57.12	0.40	0.34558			
32	4.83	41.88	7.06	5.15	88.11	100.00	57.12	0.40	0.38818			
33	5.76	43.79	7.50	5.09	88.71	100.00	57.12	0.40	0.36641			
34	6.06	35.98	7.31	5.16	90.04	100.00	57.12	0.40	0.38059			
35	5.43	45.08	7.62	5.11	88.59	100.00	57.12	0.40	0.35528			
36	5.23	40.68	7.71	5.22	88.77	100.00	57.12	0.40	0.36170			
37	5.51	45.25	7.24	5.05	87.66	100.00	57.12	0.40	0.38746			
38	4.45	43.68	7.30	5.07	89.47	100.00	57.12	0.40	0.34454			
39	4.91	44.21	7.19	5.05	88.32	100.00	57.12	0.40	0.37467			
40	6.12	45.93	7.91	4.95	89.45	100.00	57.12	0.40	0.33742			
41	5.65	40.07	7.92	4.98	89.40	100.00	57.12	0.40	0.35833			
42	5.67	38.89	7.81	5.30	88.54	100.00	57.12	0.40	0.37225			
43	5.58	43.06	7.80	5.15	89.20	100.00	57.12	0.40	0.34664			
44	4.28	42.22	7.70	5.01	88.53	100.00	57.12	0.40	0.35627			
100020	5.09	40.35	7.13	5.17	88.68	100.00	57.12	0.40	0.38382			
100021	5.02	42.54	7.78	5.12	88.97	100.00	57.12	0.40	0.34905			
100022	5.05	45.04	7.86	5.22	89.25	100.00	57.12	0.40	0.32653			
100023	5.31	41.03	7.56	5.12	90.25	100.00	57.12	0.40	0.34085			
100024	5.04	43.58	7.15	5.20	89.03	100.00	57.12	0.40	0.36053			
100025	Mean of E* Population =			0.3585								
100026	Standard Deviation of E* Population =			0.0187								

A.3 Initial Exploratory Analysis of Graded Aggregate Base

As another example of analyzing the pay factor and risk levels of different construction material, the following steps describe the process of evaluating risk factors when analyzing GAB.

Review of Current QA/QC Practice for GAB

As an example of one of the agencies that has an organized approach to the QA/QC process for the GAB, MDSHA was selected. The following are the documents that serve as a reference for QA/QC:

- Graded Aggregate Base (GAB) – Annual Plant Inspection Procedure; Deals with the annual inspection of producers providing GAB to SHA and requires inspection once a year.
- 6 Month Specific Gravity Check Procedure; Identifies the periodic evaluation of aggregate specific gravity for all state-approved GAB producing quarries.
- GAB Quality Control Plan Review Procedures; Deals with the annual approval of QC plans for each GAB producer.
- Graded Aggregate Base: Quality Assurance Audit (split gradations); Dealing with evaluation of the plants' gradation to validate the producers Quality Control (QC) results through split gradation testing.

Additional guidelines for the GAB Quality Assurance program is provided in the SHA Materials Manual (SHA MM). These include plant and field sampling and testing frequencies as outlined in the SHA Frequency Guide (Chapter II, Tables 1-4) provides additional guidelines for plant and field sampling and testing.

In addition, the policies and regulations of the Code of Federal Regulations (CFR) title 23, used by Federal Highway Administration (FHWA) were also examined which all state agencies need to follow.

Identification of key factors affecting GAB

Most agencies measure the density of the laid graded aggregate base/subbase as the mean of payment to the contractor. Although ASTM D2940 suggests 98% as the minimum average requirement, most states define their own specifications based on the job in hand. As an example, MD SHA had assigned 97% as the minimum average requirement for a portion of the ICC contract.

Even though, the density of the base/subbase is a good indication of the quality of the final product, the properties of coarse and fine aggregates used in base and subbase layers are very important to the performance of the pavement system in which they are used. The following are the minimum requirements set by ASTM D2940 that are accepted as the industry's general requirements:

1. Coarse aggregate retained on the 4.75-mm (No. 4) sieve shall consist of durable particles of crushed stone, gravel, or slag capable of withstanding the effects of handling, spreading, and compacting without degradation productive of deleterious fines. Of the particles which are retained on a 9.5-mm [3⁄8-in.] sieve, at least 75% shall have two or more fractured faces.
2. Fine aggregate passing the 4.75-mm (No. 4) sieve shall normally consist of fines from the operation of crushing the coarse aggregate. Where available and

suitable, addition of natural sand or finer mineral matter, or both, is not prohibited. The fraction of the final mixture that passes the 75-µm (No.200) sieve shall not exceed 60 % of the fraction passing the 600-µm (No. 30) sieve. The fraction passing the 425-µm (No. 40) sieve shall have a liquid limit no greater than 25 and shall have a plasticity index no greater than 4. The sand equivalent value of the fine aggregate shall be no lower than 35.

3. The gradation of the final composite mixture shall conform to an approved job mix formula, within the design range prescribed by Table 3, subject to the appropriate tolerances.
4. Base acceptance decisions upon average results obtained on samples from at least three units or batches picked at random from each lot. A lot shall be defined as not more than 3000 metric tons [3300 tons] or a full day's production for delivery to a given project.

TABLE A.3.1 Grading Requirements for Final Mixture (ASTM D2940)

Sieve Size (Square Openings)	Design Range[A] (Mass Percentages Passing)		Job Mix Tolerances (Mass Percentages Passing)	
	Bases	Subbases	Bases	Subbases
50 mm [2 in.]	100	100	–2	–3
37.5 mm [1½ in.]	95 to 100	90 to 100	±5	±5
19.0 mm [¾ in.]	70 to 92	...	±8	...
9.5 mm [⅜ in.]	50 to 70	...	±8	...
4.75 mm (No. 4)	35 to 55	30 to 60	±8	±10
600 µm (No. 30)	12 to 25	...	±5	...
75 µm (No. 200)	0 to 8[B]	0 to 12[B]	±3	±5

In addition to the general requirements set by ASTM, most state agencies define their own testing in order to assure the quality level of the aggregates purchased. The following test methods are used for the qualitative analysis of aggregate listed in the state of Maryland:

1. Specific Gravity & Absorption (ABS) of Fine Aggregate - AASHTO T 84
2. Specific Gravity & Absorption (ABS) of Coarse Aggregate - AASHTO T85
3. Abrasion & Impact by Los Angeles Machine (LA) – AASHTO T 96
4. Loose & Rodded Unit Weight - AASHTO T 19
5. Soundness by Sodium Sulfate – AASHTO T 104
6. Accelerated Polishing of Aggregate using the British Wheel (BPN) – AASHTO T 279
7. Accelerated Detection of Potentially Deleterious Expansion of Mortar Bars due to Alkali-Silica Reaction (Aggregate or Aggregate/Pozzolan Combination) (ASR) – MSMT 212

The Florida Department of Transportation (FDOT) has set the following requirements as their acceptance criteria:

1. Use material retained on the No. 10 [2.00 mm] sieve composed of aggregate meeting the following requirements:

Soundness Loss, Sodium, Sulfate: AASHTO T 104 .... 15%

Percent Wear: AASHTO T 96 (Grading A)

Group 1 Aggregates 45%

Group 2 Aggregates 65%

Group 1: This group of aggregates is composed of limestone, marble, or dolomite.

Group 2: This group of aggregates is composed of granite, gneiss, or quartzite.

2. Use graded aggregate base material meeting the following gradation:

Sieve Size	Percent by Weight Passing
2 inch [50 mm]	100
1.5 inch [37.5 mm]	95 to 100
0.75 inch [19.0 mm]	65 to 90
3/8 inch [9.5 mm]	45 to 75
No. 4 [4.75 mm]	35 to 60
No. 10 [2.00 mm]	25 to 45
No. 50 [300 µm]	5 to 25
No. 200 [75 µm]	0 to 10

3. For Group 1 aggregates, ensure that the fraction passing the No. 40 [425 µm] sieve has a Plasticity Index (AASHTO T 90) of not more than 4.0 and a Liquid

Limit (AASHTO T 89) of not more than 25, and contains not more than 67% of the weight passing the No. 200 [75 µm] sieve.

4. For Group 2 aggregates, ensure that the material passing the No. 10 [2.00 mm] sieve has a sand equivalent (AASHTO T 176) value of not less than 28.
5. The Contractor may use graded aggregate of either Group 1 or Group 2, but only use one group on any Contract.

The South Carolina Department of Transportation, currently uses the following specs for GAB:

TABLE A.3.2 Marine Limestone Base Course Gradation Specifications (Baus and Li 2006)

Sieve Designation	Percentage by Weight Passing
2"	100
1 1/2"	95 – 100
1"	70 – 100
1/2"	50 – 85
No. 4	30 – 60
No. 30	17 – 38
No. 200	0 – 20
Liquid Limit	25 Max.
Plasticity Index	6 Max.

The compaction specifications require GAB compaction at near optimum moisture until the entire base course is compacted to not less than 100% of maximum laboratory density as determined by AASHTO T 180 (Method D). If the total compacted thickness of the graded aggregate base course is more than 8 inches (a condition not allowed by current SCDOT design practice), the base course should be compacted in two or more layers of approximately equal thickness.

The SCDOT uses AASHTO flexible pavement design methods and Structural Number (SN) to quantify pavement structure. The GAB layer's contribution to SN is the product of GAB layer thickness D_2 (in inches) and layer coefficient a_2 (in 1/inches). The value of layer coefficient quantifies the material quality (influenced by the material's mineralogy, gradation, and other factors that affect mechanical properties) and is a measure of the ability of a unit thickness of the material to function as a structural component of the pavement. Layer coefficient may also be influenced by layer thickness, layer location in the pavement structure, traffic level, and failure criterion (Appendix GG, AASHTO 1986).

A well-known relationship between a_2-value for untreated granular base course materials and resilient modulus (MR) was developed by Rada and Witczak (1981). The relationship is:

$a_2 = 0.249 \times \log(M_R) - 0.977$ where M_R is the Resilient Modulus

A study performed for SCDOT (Investigation of Graded Aggregate Base Courses 2006), has summarized the Compaction Standards and the gradation requirements for several states that participated in their survey.

TABLE A.3.3. Compaction Standards (Baus and Li 2006)

State Name	Compaction Specification
Maine	95% AASHTO T 180 C or D, and corrected by Adjustment Chart
Illinois	100% AASHTO T 99 and corrected by AASHTO T 224
Washington	95% WSDOT Test Method
Alaska	98% AASHTO T 180 D
Indiana	100% AASHTO T 99
New Hampshire	95% AASHTO T 99
Utah	97% AASHTO T 180 D +/-2% optimum water content
Wisconsin	AASHTO T 99 C, (replacement of the fraction)

TABLE A.3.4. Grading Requirements for No.4 and No. 200 Sieves (Baus and Li 2006)

State Name	Percent Passing			
	No. 4 Sieve		No. 200 Sieve	
	Low Limit	High Limit	Low Limit	High Limit
Delaware	20	50	N/A	N/A
Washington	25	N/A	N/A	N/A
Florida	35	60	0	10
Tennessee	35	55	N/A	N/A
Alaska	30	60	0	6
Nebraska	N/A	93	N/A	3
New Hampshire	25	52	0	12
South Carolina	30	50	0	12

Under NCHRP Project 4-23, "Performance-Related Tests of Aggregates for Use in Unbound Pavement Layers," the researchers identified aggregate properties that influence the performance of pavements; identified and evaluated, in a laboratory investigation, the aggregate tests currently used in the United States and other countries as well as potential new aggregate tests to measure performance-related properties.

This NCHRP Project 4-23 has summarized the majority of the aggregate tests with a subjective, qualitative rating for each test method. The rating in each category for each test method was based on the research team's experience and judgment.

TABLE A.3.5. Rating of Potential Test Methods (NCHRP Project 4-23)

Property Measured	Test Name	Performance Predictability	Accuracy	Practi-cality	Com-plexity	Precision	Cost	Composite
Shear Strength	Static Triaxial Shear	F	G	H	FS	G	M	H
	Repeated Load Triaxial	G	G	H	C	G	M	H
	Texas Triaxial	F	G	M	FS	F	M	M
	Illinois Rapid Shear	F - G	G	M	FS	G	M	M – H
	Confined Compression	F	F	H	S	F	L	M
	Direct Shear	F	F	L	FS	F	M	L
	Gyratory Shear	F	F	M	C	F	M	M
	k-Mould	G	G	M	C	F	M	M - H
	CBR	F	G	M	S	F	L	M - H
	Hveem Stabilometer	F	F	M - H	S	F	L	L - M
	Hollow Cylinder	G	G	L	VC	L	H	L
	Dynamic Cone Penetrometer	F	F	M	S	F	L	M
	Lab Rut-Tester	G	F	L	C	F	H	L - M
Stiffness	Resilient Modulus	F	F	L	C	F	M	H
	Variable Confining Pressure Modulus	F	F	L	VC	F	H	M
	Resonant Column	P	P	L	C	P	M	L
Frost Susceptibility	Frost Susceptibility Test	F	F	L	C	P - F	H	L
	Index Tests	F	G	H	S	F	L	M
Permeability	Constant Head	F	F	M	FS - S	F	L	M
	Falling Head	F	F	H	FS	F	L	M
	Pressure Chamber	F	F	H	FS	F	M	L – M
	Horizontal Permeameter	F	G	H	FS	G	M	M
Toughness	LA Abrasion	F	F	H	S	F	L	M
	Aggregate Impact Value	F	G	H	S	G	L	M
	Aggregate Crushing Value	G	G	H	S	F	L	M – H
	Aggregate Abrasion Value	F	F	H	FS	F	L	M - H
	Micro-Deval	G	F	H	F	F	L	H
	Durability Mill	F	G	H	FS	F	L	M
	Gyratory Test	F	G	H	FS	F	M	M – H
Durability	Sulfate Soundness	F	F	H	F	F	L	M – H
	Freezing and Thawing	G	G	M	FS	F	M	M - G
	Canadian Freeze-Thaw	G	G	M	FS	F	M	M
	Aggregate Durability Index	F	F	H	FS	F	L	M - H
	Unconfined Freeze Thaw	F	F	H	FS	F	M	M
Mineralogical Composition	Petrographic Examination	F	F	L	C	F	H	L - M
Particle Geometric Properties	Particle Shape and Surface Texture Index	F	F	M	S	F	L	M
	Flat and Elongated Particles	P	F	L	S	F	L	M
	Percentage of Fractured Particles	G	G	H	FS	F	L	M – H
	Uncompacted Void Content	F	F	M	S	F	L	M
	Digital Image Analysis	P	F	M	C	F	H	L – M
	Atterberg Limits	F	G	M	S	F	L	M
	Sand Equivalent Test	F	F	M	S	F	L	M
	Methylene Blue Test	F	G	M	F	F	L	M

Rating Scale:
Performance Predictability - G = good, F = fair, P = poor
Accuracy - G = good, F = fair, P = poor
Practicality - H = high, M = medium, L = low
Complexity Levels - S = simple, FS = fairly simple, C = complex, VC = very complex
Precision - G = good, F = fair, P = poor
Cost - H = high, M = medium, L = low
Composite – H = high, M = medium, L = low (based on relative ratings of other factors)
Note: All ratings are "average" subjective evaluations of research team. The composite rating is based on the relative ratings for each category.

Based on sections 3.1.1 and 3.1.2 it can be determined that the single main parameter to measure the quality of GAB is its field density. It can also be concluded that this parameter is mainly affected by the gradation of the aggregates used in the mix and also the moisture content. Due to the low tolerances assigned by ASTM to sieves No.

30 and No. 200, and the importance of the 3/8 in sieve in differentiating between fine and coarse aggregate, these three sieve sizes, the moisture content (MC) and the measure field density will be used as the key factors.

The following table summarizes the parameters that will be adjusted in order to see the effect based on the given range on the final outputs such as Type I and Type II error.

TABLE A.3.6. Quality Indicators for GAB and Range of Values

GAB Quality Indicators	Range of Values[1]	Potential Distribution[2]
ABS of Fine Aggregate	0.4% - 8.0%	
ABS of Coarse Aggregate	0.2%-12.0%	
Degradation (LA Abrasion)	% Loss: 10-50	
Loose Unit Weight (Fine Agg)	80-110 lb/ft^3	
Rodded Unit Weight (Fine Agg)	90-130 lb/ft^3	
Loose Unit Weight (Coarse Agg)	45-105 lb/ft^3	
Rodded Unit Weight (Coarse Agg)	50-114 lb/ft^3	
Soundness	% Loss: 0.1-20	
BPN	0-150	
ASR	% Length Change: 0.01-0.35	
Sieve Size 50mm	% Passing: 98 - 100	Normal, Weibull
Sieve Size 37.5mm	% Passing: 90 - 100	Normal, Weibull
Sieve Size 19mm	% Passing: 62 - 100	Normal, Weibull

Sieve Size 9.5mm	% Passing: 42 - 78	Normal, Weibull
Sieve No.4	% Passing: 20 - 93	Normal, Weibull
Sieve No.30	% Passing: 7 - 42	Normal, Weibull
Sieve No.200	% Passing: 0 - 20	Normal, Weibull
Sieve 3/8 in	% Passing: 42 - 75	Normal, Weibull
Field Density	90%-100%	Normal, Weibull
Plasticity Index (passing No.40)	0-6	Normal, Weibull
Liquid Limit (passing No.40)	0-25	Normal, Weibull
Sand Equivalent (passing No.4)	28-100	Normal, Weibull
Resilient Modulus	30,000 – 50,000 psi	N/A
Fractured Faces	>2	N/A
Correlation range among Parameters	-1 to 1	N/A

Note:

1- Three or more level of values will be considered in this analysis representing low, medium and high.

2- Different groups of Weibull distributions will be considered, to represent a wide range of scale and shape parameters

Correlation among key factors

As determined in the previous section, parameters such as sieves No.30, No. 200, the 3/8 in sieve, the MC, the field density and other parameters as described in Table 8 are the key factors of the GAB.

A parameter/factor that incorporates all of the mentioned key factors does not exist. Therefore, since ultimately the agencies prefer to look at the risks in terms of their pay, the following pay factor is proposed to incorporate all of the key factors:

$$PF = \frac{f1*PWL1 + f2*PWL2 + f3*PWL3+f4*MC+f5*FD}{\Sigma f}$$

where:

f_1=weight of sieve No.30

f_2=weight of sieve No.200

f_3=weight of sieve 3/8 in

f_4=weight Moisture Content

f_5=weight of Field Density

PWL_1=Percent Within Limit of sieve No.30

PWL_2=Percent Within Limit of sieve No.200

PWL_3=Percent Within Limit of sieve 3/8 in

MC = Moisture Content (%)

FD= Field Density (%)

In a study by Burati (2005) 1742 sets of test results were analyzed for correlations. In this study the specifications of SCDOT were investigated. SCDOT uses four parameters; AC, AV, VMA and in-place density from cores to determine payment for HMA. The composite pay factor that SCDOT uses to calculate the composite pay factor is:

$$LPF = 0.25(PF_{AC}) + 0.30(PF_{AV}) + 0.10(PF_{VMA}) + 0.35(PF_{DEN})$$

This equation assumes that the four parameters are statistically independent. To investigate any possible correlations project test results were analyzed by Burati. The correlations of the following pairs were analyzed: AC-AV, AC-VMA, and AV-VMA and the correlation values are summarized in the following table.

TABLE A.3.7 Correlation Coefficients for all Pairs of Plant Quality Characteristics (Burati 2005)

	AC	AV	VMA
AC	—[a]	0.247	0.856
AV	0.247	—[a]	0.691
VMA	0.856	0.691	—[a]

[a]Not applicable.

A computer simulation program (PAYSIM2) was used by Burati to compare the effect of these correlations on the average payments. The results showed that on average the payments tend to be the same in both cases (with and without the correlations). Table 11 illustrates these effects.

TABLE A.3.8. Effects of Correlations between Variables Using Simulation Analysis (Burati 2005)

Quality Characteristics Simulated	Correlation Coefficient	Average Composite Payment Factor[a]	Standard Deviation of Composite Payment Factors[a]
AC and AV	0.000	55.04	2.12
AC and AV	0.247	55.02	2.18
AC and VMA	0.000	35.01	1.46
AC and VMA	0.856	35.04	1.78
AV and VMA	0.000	40.04	1.72
AV and VMA	0.691	39.95	1.98

[a] Sample size = 5.
Both simulated populations had 90 PWL.
5000 lots were simulated for each pair of variables.

In a recent research project on HMA mixtures (Karimi, 2009), based on the correlation coefficients for dense graded mixtures for HMA, several analyses show that their effects had no impact on the pay factor analysis. In the example of Table 12 the values of the correlations were changed ranging from 0.001 to 0.999. As it can be seen no effects on the average PF were observed, however, the standard deviation decreased with an increase in the correlation between parameters.

TABLE A.3.9. Example of Effect of Correlation Value on the Average PF

Average CPWL	Std. Dev. CPWL	Average PF	Std. Dev. PF	Correlation
86.2	10.3	98.1	5.2	0.999
86.2	8.0	98.1	4.0	0.5
86.0	7.2	98.0	3.6	0.001
86.2	7.5	98.1	3.8	Population

The same approach will be undertaken in this study. Correlation values ranging from 0 to 1 is considered in order to study the effect on PF. As an example, the data provided by MD SHA from the ICC contract were examined and as shown below the correlation between the field density and MC data is calculated to be -0.47. The scatter of data is illustrated below, recognizing the fact that these data do not represent the full range of moisture effects on density, but the achieved field density data once the optimum moisture content for this base was identify.

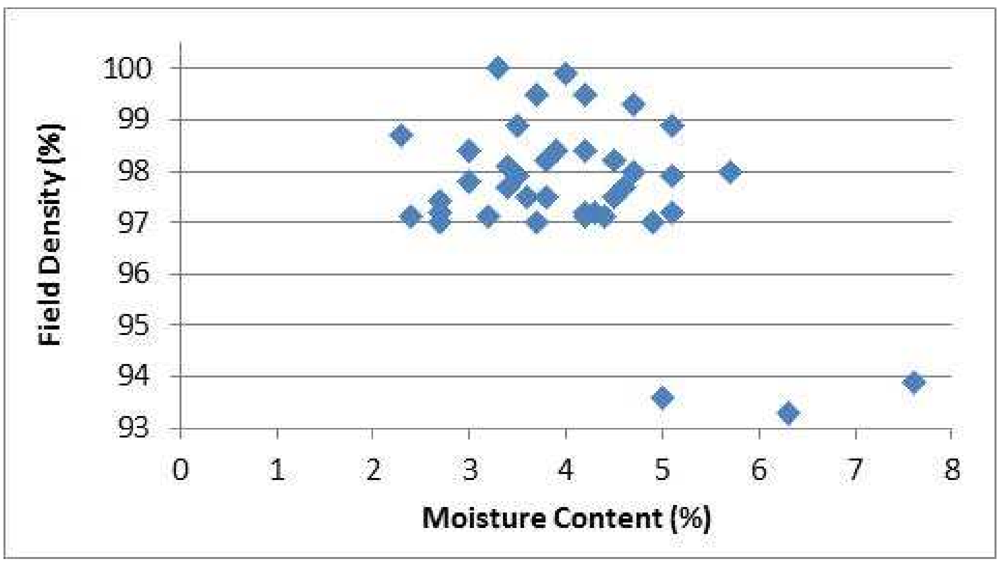


FIGURE A.3.1. Correlation Analysis for ICC Density Data vs. MC.

Figure below is an example of how the MC and the unit weight are related to each other and how their correlation changes from positive to negative passed the peak of the curve (the optimum MC). Thus, it is reasonable to consider a range of -1 to 1 for the correlation coefficient between field density and MC.

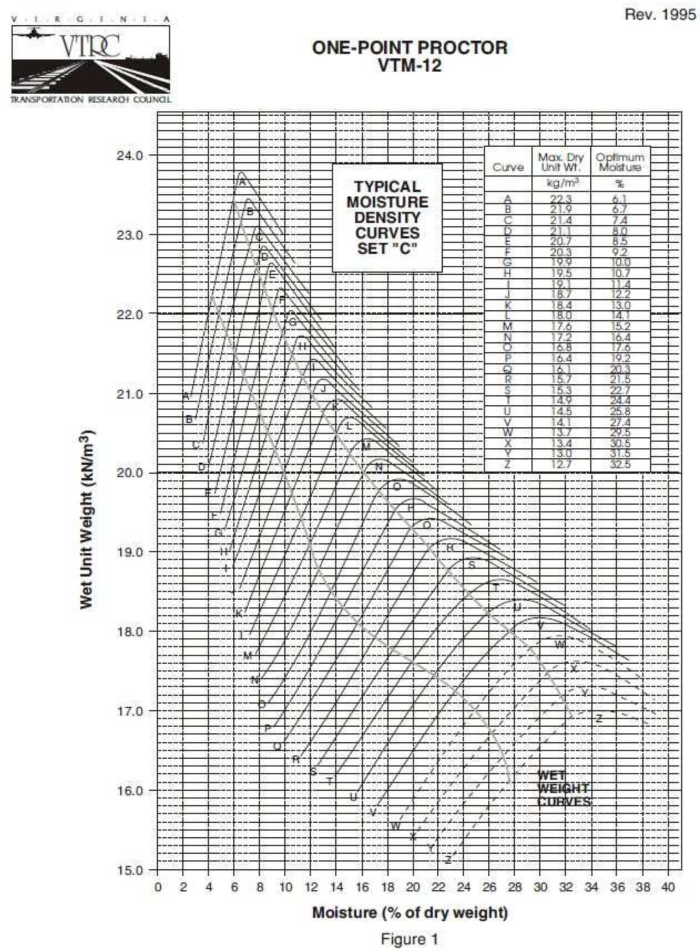


FIGURE A.3.2. Typical Moisture Density Curves (Virginia Transportation Research Council, 1995)

OC Curves

To follow on with the data used in the example described in section 3.1.4 the procedure set forth by Villiers et al. (2003) which was described in detail in section 2.5.2 and using the standard error of the population will be used in order to relate PWL and probability of acceptance. Based on the characteristics of all the QA data (average of 98.2% and standard deviation of 0.89), simulation analysis were run for various sample sizes (n) and using the 20 normally distributed QA data. Figure 13 shows four OC curves for different values of n.

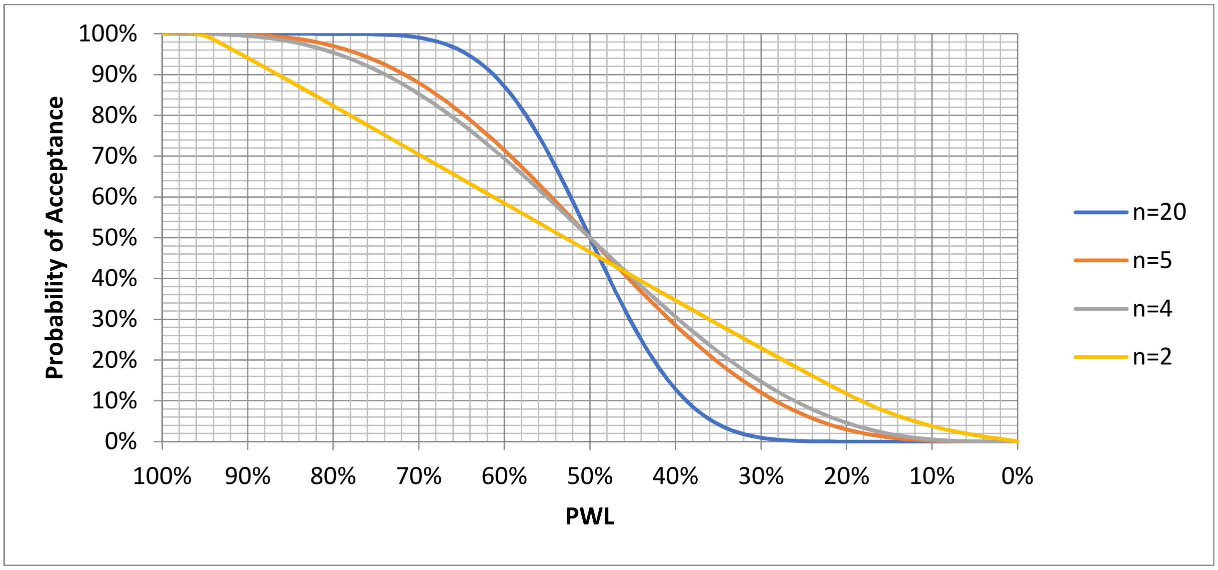


FIGURE A.3.4. OC Analysis for ICC Density Data.

The alpha and beta values were calculated based on AQL and RQL of 90% and 40% and are tabulated below.

TABLE A.3.10. Risk Values for ICC Individual Density Data.

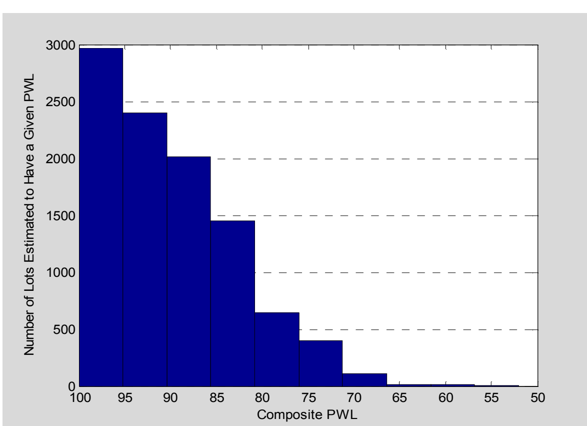
Sample size	Alpha (%)	Beta (%)
20	0	13
5	0	29
4	1	30
2	4	37

As discussed, alternative data distributions will be considered for generating new OC curves and thus examining the impact on alpha and beta risks, providing the bases for risk analysis and impact on pay factors.

Pay factor analysis

Using the pay schedule equations, as discussed in section 3.1.3 pay factor analysis will be performed for different quality indicator values, parameter distributions, spec tolerances and correlations between the variables. Thus, through MATLAB programming, the effects of different distributions for each parameter will be examined on the final pay factor, along with the effects of changing specification tolerances and correlation values.

Figures 14 and 15 are included herein as a simple example of pay factor analysis and implications. The analysis was developed for Gap Graded HMA at two different levels of production, AQL and RQL. For example, it can be seen that as the production levels move from AQL to RQL, the average Pay Factor reduces from 1.00 to .041. Such analysis will be performed for the above parameters and the results will be used for relevant conclusions.



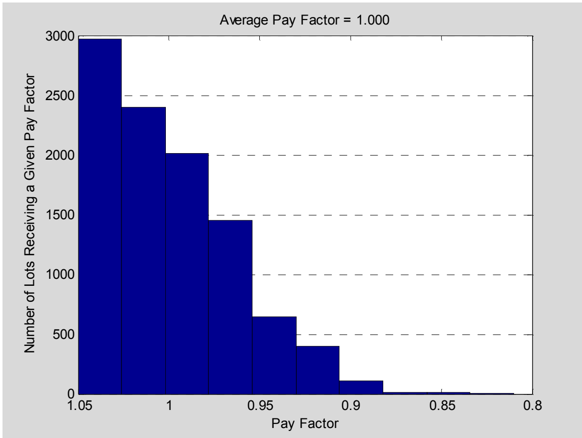


FIGURE A.3.5. Gap Graded PWL and Pay Factor Distribution for Production at AQL

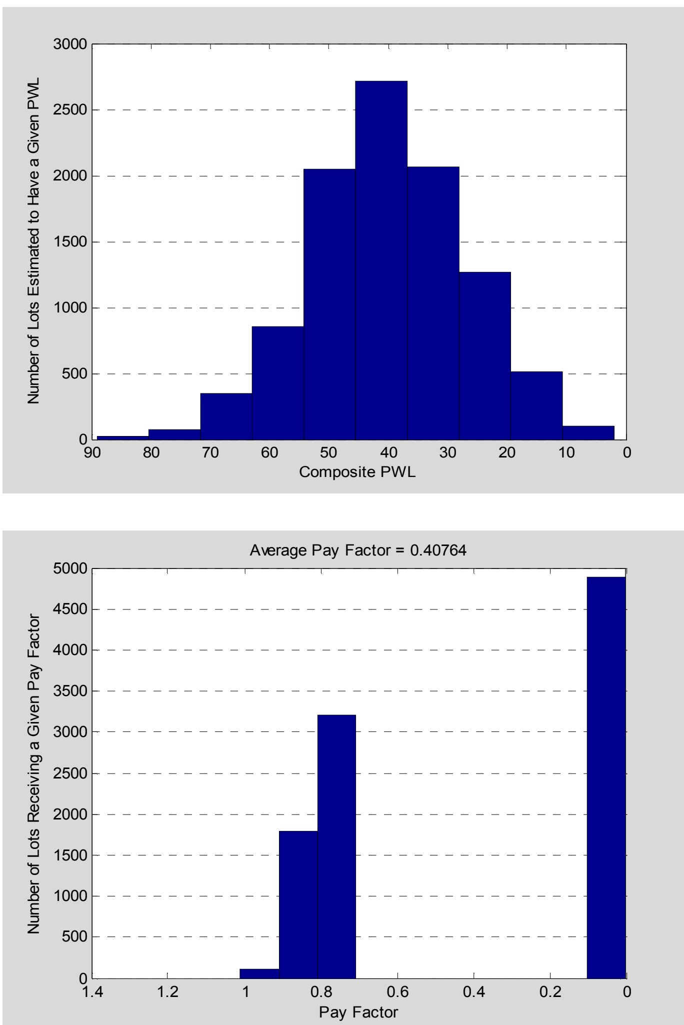


FIGURE A.3.6. Gap Graded PWL and Pay Factor Distribution for RQL

*** THIS PAGE IS INTENTIONALLY LEFT BLANK ***

References

Baker T., R. Molohon, and R. Mclntyre, “Materials Risk Analysis” Washington Department of Transportation (WSDOT), Report WA-RD 745.1, 2010

Burati J., “Risks with Multiple Pay Factor Acceptance Plans,” Transportation Research Record No. 1907, Transportation Research Board of the National Academies, Washington, D.C., 2005

Burati J., “Evaluating Specification Limits,” Transportation Research Record No. 1946, Transportation Research Board of the National Academies, Washington, D.C., 2006

Burati J., and R. Weed, “Accuracy and Precision of Typical Quality Measures,” Transportation Research Record No. 1946, Transportation Research Board of the National Academies, Washington, D.C., 2006

Burati J., R. Weed, C. Hughes, and H. Hill, “Optimal Procedures for Quality Assurance Specifications” Federal Highway Administration (FHWA), Report FHWA-RD-02-095, 2003

“Glossary of Highway Quality Assurance Terms,” *Transportation Research Circular No. E-C037*, Transportation Research Board, Washington, DC, 2002

Karimi S., “Increasing Durability of Hot Mix Asphalt Pavements Designed with the Superpave System”, University of Maryland, 2009

Karimi S., D. Goulias, and C. Schwartz., Evaluation of Superpave HMA Mixture Properties at the Plant versus behind the Paver: Statistical Comparison of QC and QA Data., Journal of Transportation Engineering, 2012

Mahoney J, and S. Muench “A Quantification and Evaluation of WSDOT’s Hot Mix Asphalt Concrete Statistical Acceptance Specification” Washington State Transportation Center, Report T9903.2, 2001

Maryland Department of Transportation State Highway Administration Office of Materials and Technology Maryland Standard Method of Tests “MSMT 457 – Sampling Hot Mix Asphalt Prior to Compaction” 2005

Maryland Department of Transportation State Highway Administration Office of Materials and Technology Maryland Standard Method of Tests “MSMT 733 – Procedure for Evaluating HMA Lot Compaction for Compliance” 2002

Maryland Department of Transportation State Highway Administration Office of Materials and Technology Maryland Standard Method of Tests “MSMT 734 – Procedure for Determining Statistical Outliers” 2004

Maryland Department of Transportation State Highway Administration Office of Materials and Technology Maryland Standard Method of Tests “MSMT 735 – Statistical Analysis of Material Using Quality Level Analysis for Determination of Pay Factors” 2008

NCHRP Project No. 10-79: “Guidelines for Quality-Related Pay Adjustment Factors For Pavements”, Washington Dc., 2011

NCHRP Report 455: “Recommended Performance-Related Specification for Hot-Mix Asphalt Construction: Results of the WesTrack Project”, Washington DC., 2002

NCHRP Report 704: “A Performance-Related Specification for Hot-Mixed Asphalt”, Washington DC., 2011

NCHRP Report 838: “Guidelines for Optimizing the Risk and Cost of Materials QA Programs”, Washington DC., 2017

NCHRP Report 946: “Procedures and Guidelines Validating Contractor Test Data”, Washington DC., 2020

NCHRP Synthesis 346: “State Construction Quality Assurance Programs - A Synthesis of Highway Practice”, Washington DC., 2005

Parker F., and R. E. Turochy, “Using the Results of Contractor-Performed Tests in Quality Assurance,” NCHRP Research Results Digest 323, Transportation Research Board of the National Academies, 2007

Quality Assurance Guide Specification. AASHTO, Washington, D.C., 1996

Sholar G. A., G. C. Page, J. A. Musselman, P. B. Upshaw, and H. L. Moseley, “Development of the Florida Department of Transportation’s Percent Within Limits Hot-Mix Asphalt Specification” Transportation Research Board Record No. 1907, pp. 43-51, Transportation Research Board of the National Academies, Washington, D.C., 2005

Turochy R., R. Willis, and F. Parker, “Quality Assurance of Hot-Mix Asphalt Comparison of Contractor Quality Control and Georgia Department of Transportation Data,” Transportation Research Record No. 1946, Transportation Research Board of the National Academies, Washington, D.C., 2006

Villiers C., Y. Mehta, G. Lopp, M. Tia, and R. Roque, “Evaluation of Percent-within-limits- Construction Specification Parameters,” International Journal of Pavement Engineering, pp. 221-228, London, U.K., 2003

Wazalwar G., “Methodology to Develop a Minimum Cost Acceptance Sampling Plan for Highway Construction” University of Texas at El Paso., 2009

Weed, R.M., “Quality Assurance Software for the Personal Computer,” *Publication*

No. FHWA–SA–96–026, Federal Highway Administration, Washington, DC, May 1996.

Zhao, Y., Goulias D. "Evaluation of Acceptance Risks through Percent within Limit for Highway Materials and Pavement Construction," Transportation Research Record Journal, 2021

Zhao, Y., Goulias D. "Pay Factor Analysis for Highway Pavements through Percentage of Material within Specification Limits and Monte Carlo Simulation," Transportation Research Record Journal, 2021

Zhao, Y., Goulias D. "Risk and Pay Factor Assessment of Using Contactor Quality Control Data for Acceptance." Transportation Research Record 101 Annual Meeting, to be presented January 2022