MD-09-SP708B4E

Martin O'Malley, *Governor*
Anthony G. Brown, *Lt. Governor*

State Highway Administration
Maryland Department of Transportation

Beverley K. Swaim-Staley, *Secretary*
Neil J. Pedersen, *Administrator*

STATE HIGHWAY ADMINISTRATION

RESEARCH REPORT

Increasing Durability of Hot Mix Asphalt Pavements Designed with the Superpave System

Dr. Dimitrios Goulias (PI)
Dr. Charles Schwartz (Co-PI)
Sahand Karimi (Graduate Research Assistant)
University Of Maryland

Chuck Hughes
Consultant

Project number SP708B4E

FINAL REPORT

June 30, 2009
August 25, 2009 (rev)

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Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
MD-09-SP708B4E		

4. Title and Subtitle	5. Report Date
Increasing Durability of Hot Mix Asphalt Pavements Designed with the Superpave System	August 25, 2009
	6. Performing Organization Code
7. Author/s	8. Performing Organization Report No.
Dimitrios Goulias, Charles Schwartz, Sahand Karimi, & Chuck Hughes	
9. Performing Organization Name and Address	10. Work Unit No. (TRAIS)
University of Maryland 0147A G.L. Martin Hall College park, MD 20742	11. Contract or Grant No. SP708B4E
12. Sponsoring Organization Name and Address	13. Type of Report and Period Covered
Maryland State Highway Administration Office of Policy & Research 707 North Calvert Street Baltimore MD 21202	Final Report
	14. Sponsoring Agency Code 7120) STMD - MDOT/SHA

15. Supplementary Notes

16. Abstract

Maryland SHA's concern with the lower asphalt levels in HMA mixes have lead efforts to explore strategies to increase the asphalt content in Superpave mixes. National studies identified methods for adjusting binder content without compromising rutting performance of asphalt mixtures and remaining loyal to the Superpave philosophy. The applicability of these methods to SHA conditions were addressed based on the findings of recent National Cooperative Highway Research Program projects, ongoing discussions with SHA engineers, and experts' feedback in this area. Furthermore, this study addressed the differences in HMA properties that have been observed over the years between samples taken at the plant versus behind the paver. A large set of SHA QA and QC data was analyzed statistically in the context of current specifications and pay factors to evaluate potential risks to both SHA and contractors. The research team developed the Operating Characteristic (OC) curves based on the QA data and for estimating the risks to SHA and contractors (Type I and II risks). With the aid of a new simulation tool the associated pay factors were analyzed using the population characteristics and considering potential correlations between the HMA mix parameters.

17. Key Words	18. Distribution Statement: No restrictions
Quality Assurance, quality control, specifications, Pay Factor, Superpave Mix Design	This document is available from the Research Division upon request.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. Of Pages	22. Price
None	None	128	

Form DOT F 1700.7 (8-72) Reproduction of form and completed page is authorized.

University of Maryland, College Park

Department of Civil and Environmental Engineering

Increasing Durability of Hot Mix Asphalt Pavements Designed with the Superpave System

Final Research Report

Maryland State Highway Administration

Research Project SP708B4E

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TABLE OF CONTENTS

LIST OF FIGURES ..... **I**

LIST OF TABLES ..... **IV**

CHAPTER 1 ..... **1**

1.1 Introduction **1**

1.2 Research Approach **2**
1.2.1 Increasing the Durability of Superpave Mixes 2
1.2.2 Review of QA/QC Data, Risk and Expected Pay Analysis 3

1.3 Organization of the Report **4**

CHAPTER 2 LITERATURE REVIEW **5**

2.1 Improving Durability of Superpave HMA Mixtures **5**
2.1.1 Durability Basics 5
2.1.2 State of the Literature 6
Overall Findings 7
Binder Content 8
Design Air Voids 10
In-Place Air Voids 11
VMA 13
Permeability 13
Age Hardening 14
Summary 15
2.1.3 Implications for Maryland SHA Practice 17

2.2 Quality Measures for HMA Mixtures **21**
2.2.1 Introduction 21
2.2.2 Comparison of QA and QC data (F and *t* test) 21
2.2.3 Quality Indicators 24
2.2.4 Evaluating Specification Limits 26
2.2.5 Risk Analysis and Pay Factor Evaluation 28

CHAPTER 3 COMPARISON OF QA & QC DATA **34**

3.1 F and *t* Tests **34**
3.1.1 Initial Exploratory Assessment Using Random Projects 34
3.1.3 Analysis Based on Mixtures Type and Property (Matched Lots and Sublots) 36

3.1.4 Unpaired vs. Paired Analysis based on Mixture Type and Property (Matched Lots and Sublots) 37
3.1.5 Analysis based on Mixtures Type, Mix Property, and Mix Band 38
3.1.6 Analysis based on Deviations from the Target Values 39

3.2 Transfer Functions Between QA and QC Data 44

CHAPTER 4 TYPE I AND TYPE II ERROR ANALYSIS & OPERATION CHARACTERISTIC (OC) CURVES 45

4.1. Definitions 45

4.2. Construction of OC Curves and Calculation of Type I and Type II Errors 48
4.2.1 Assessing the Current Conditions 48
4.2.2 Modifying AQL and RQL to balance the risks (α= 1% and β= 5%) 51
4.2.3 Revised Specification Tolerances for α= 1% and β= 5% 51

CHAPTER 5 SIMULATION ANALYSIS 53

5.1 Analysis Based on Previous Specifications 54
5.1.1 Reducing Asphalt Content Variability 54
5.1.2 Modifying Specification Tolerances 56
5.1.3 Population Characteristics and Effects on CMPSWL and MF 61

5.2 Analysis Based on Current Specification (with Bonus Provision) 62
5.2.1 Reducing Asphalt Content Variability 63
5.2.2 Modifying Specification Tolerances 64
5.2.3 Population Characteristics and Effects on CMPSWL and MF 67

5.3 Other Analysis 68

CHAPTER 6 PAY FACTOR ANALYSIS 70

6.1 Dense Graded HMA 70
6.1.1 Mixture Expected Pay Analysis 70
6.1.2 Improving Production Quality & Potential Modifications in Spec Tolerances 81

6.2 Gap Graded HMA 85
6.2.1 Mixtures Expected Pay Analysis 85

6.3 Density Analysis 91

CHAPTER 7 SUMMARY, CONCLUSIONS & RECOMMENDATIONS 97

7.1 Summary 97

7.2 Conclusions 99

7.3 Recommendations **101**

REFERENCES **104**

APPENDIX **108**

A. Simulation Tool **108**
A.1 Description of the Simulation Process 108
A.2 MATLAB Codes of the Simulation Tool for HMA Mix Properties 110
A.3 MATLAB Codes of the Simulation Tool for the Density Analysis 113
A.4 Implications of Correlation Coefficients on PF 118

B. Impact of Reducing Population Variability and/or Modifying Spec Tolerances **119**

C. Alternative Approach for Defining HMA Specifications **120**

LIST OF FIGURES

FIGURE 2.1 EFFECT OF DESIGN VBE ON RELATIVE IN-SITU FATIGUE LIFE 9
FIGURE 2.2 EFFECT OF AGGREGATE FINENESS AND DESIGN VMA ON RUT RESISTANCE OF SUPERPAVE MIXTURES AT A CONSTANT IN-PLACE AIR VOID CONTENT OF 7% 9
FIGURE 2.3 EFFECT OF DESIGN VMA AND AIR VOIDS ON RUT RESISTANCE OF SUPERPAVE MIXTURES AT CONSTANT IN-PLACE AIR VOID CONTENT 10
FIGURE 2.4. EFFECT OF DESIGN AIR VOIDS AND DESIGN VMA ON RELATIVE IN-SITU FATIGUE LIFE AT CONSTANT IN-PLACE AIR VOIDS 10
FIGURE 2.5 EFFECT OF BINDER GRADE AND N_{DESIGN} ON RUT RESISTANCE AT 4% DESIGN AIR VOIDS AND 7% IN-PLACE AIR VOIDS 11
FIGURE 2.6 EFFECT OF VMA AND IN-PLACE AIR VOIDS ON RUT RESISTANCE OF SUPERPAVE MIXTURES AT CONSTANT DESIGN AIR VOID CONTENT 12
FIGURE 2.7 EFFECT OF IN-PLACE AIR VOIDS AND DESIGN AIR VOIDS ON RELATIVE IN-SITU FATIGUE LIFE 12
FIGURE 2.8 PERMEABILITY OF SPECIMENS AND NCHRP PROJECTS 9-25 AND 9-31 AS A FUNCTION OF EFFECTIVE AIR VOID CONTENT 14
FIGURE 2.9 PREDICTED MIXTURE AGE-HARDENING RATIO AT 25°C AND 10 HZ AS A FUNCTION OF IN-PLACE AIR VOID CONTENT AND FM_{300} FOR A MAAT OF 15.6^{O}C 15
FIGURE 2.10 CONTACTOR AND OWNER RISK USING UNKNOWN STANDARD DEVIATION. 29
FIGURE 3.1 DEVIATIONS FROM THE TARGET VALUES FOR AC 40
FIGURE 3.2 DEVIATIONS FROM THE TARGET VALUES FOR 4.75MM 40
FIGURE 3.3 DEVIATIONS FROM THE TARGET VALUES FOR 2.36MM 41
FIGURE 3.4 DEVIATIONS FROM THE TARGET VALUES FOR 0.075MM 41
FIGURE 3.5 COMPARISON OF QA & QC DATA FOR THE 0.075MM OF THE 12.5 GAP GRADED MIXTURES 45
FIGURE 3.6 COMPARISON OF QA & QC DATA FOR THE 2.36 MM OF THE 12.5 GAP GRADED MIXTURES 45
FIGURE 3.7 COMPARISON OF QA & QC DATA FOR THE 4.75MM OF 12.5 GAP GRADED MIXTURES 45
FIGURE 3.8 COMPARISON OF QA & QC DATA FOR THE AC CONTENT OF 12.5 GAP GRADED MIXTURES 46
FIGURE 4.1 OC CURVE FOR 0.075 MM OF GAP GRADED MIXTURES 49
FIGURE 4.2 OC CURVE FOR 2.36 MM OF GAP GRADED MIXTURES 49
FIGURE 4.3 OC CURVE FOR 4.75 MM OF GAP GRADED MIXTURES 50
FIGURE 4.4 OC CURVE FOR AC CONTENT OF GAP GRADED MIXTURES 50
FIGURE 5.1 EFFECT OF REDUCTION IN ASPHALT CONTENT VARIABILITY 55
FIGURE 5.2 EFFECT OF REDUCTION IN ASPHALT CONTENT VARIABILITY ON MF 55
FIGURE 5.3 EFFECT OF REDUCTION IN ASPHALT CONTENT VARIABILITY ON CMPWSL 56
FIGURE 5.4 EFFECTS OF CHANGE IN AC SPECIFICATION TOLERANCE ON CMPWSL 57
FIGURE 5.5 EFFECTS OF CHANGE IN AC SPECIFICATION TOLERANCE ON MF 57
FIGURE 5.6 EFFECTS OF CHANGE IN 0.075 SPECIFICATION TOLERANCE ON CMPWSL 58
FIGURE 5.7 EFFECTS OF CHANGE IN 0.075 SPECIFICATION TOLERANCE ON MF 58
FIGURE 5.8 EFFECTS OF CHANGE IN 2.36 SPECIFICATION TOLERANCE ON CMPWSL 59
FIGURE 5.9 EFFECTS OF CHANGE IN 2.36 SPECIFICATION TOLERANCE ON MF 59
FIGURE 5.10 EFFECTS OF CHANGE IN 4.75 SPECIFICATION TOLERANCE ON CMPWSL 60
FIGURE 5.11 EFFECTS OF CHANGE IN 4.75 SPECIFICATION TOLERANCE ON MF 61
FIGURE 5.12 CMPSWL AND MF FOR DIFFERENT MIXTURES USING PAY EQUATION 5.1 62
FIGURE 5.13 EFFECT OF REDUCTION IN AC CONTENT VARIABILITY ON MF 63
FIGURE 5.14 EFFECTS OF CHANGE IN AC SPECIFICATION TOLERANCE ON MF 64
FIGURE 5.15 EFFECTS OF CHANGE IN 0.075 SPECIFICATION TOLERANCE ON MF 65

FIGURE 5.16 EFFECTS OF CHANGE IN 2.36 SPECIFICATION TOLERANCE ON MF 66
FIGURE 5.17 EFFECTS OF CHANGE IN 4.75 SPECIFICATION TOLERANCE ON MF 67
FIGURE 5.18 CMPSWL AND MF FOR DIFFERENT MIXTURES USING BONUS PROVISION 68
FIGURE 5.19 VARIABILITY IN ASPHALT CONTENT BY VARIOUS PLANTS IN MARYLAND . 69
FIGURE 6.1 DISTRIBUTION OF ASPHALT CONTENT POPULATION AND THE TOLERANCES 70
FIGURE 6.2 DISTRIBUTION OF PASSING 0.075MM POPULATION AND THE TOLERANCES ... 71
FIGURE 6.3 DISTRIBUTION OF PASSING 2.36MM POPULATION AND THE TOLERANCES 71
FIGURE 6.4 DISTRIBUTION OF PASSING 4.75MM POPULATION AND THE TOLERANCES 72
FIGURE 6.5 DISTRIBUTION OF ASPHALT CONTENT AT AQL 72
FIGURE 6.6 DISTRIBUTION OF ASPHALT CONTENT AT RQL 73
FIGURE 6.7 DISTRIBUTION OF PASSING 0.075MM AT AQL 73
FIGURE 6.8 DISTRIBUTION OF PASSING 0.075MM AT RQL 74
FIGURE 6.9 DISTRIBUTION OF PASSING 2.36MM AT AQL 74
FIGURE 6.10 DISTRIBUTION OF PASSING 2.36MM AT RQL 75
FIGURE 6.11 DISTRIBUTION OF PASSING 4.75MM AT AQL 75
FIGURE 6.12 DISTRIBUTION OF PASSING 4.75MM AT RQL 76
FIGURE 6.13 EP CURVES WITH EXPECTED PF USING POPULATION CHARACTERISTICS 77
FIGURE 6.14 CMPWL AND PAY FACTOR DISTRIBUTION FOR PRODUCTION “CLOSE TO” AQL (MAX CMPWL = 88.7 USING POPULATION STANDARD DEVIATION) 79
FIGURE 6.15 CMPWL AND PAY FACTOR DISTRIBUTION FOR RQL (WITH POPULATION STANDARD DEVIATION) 80
FIGURE 6.16 EP CURVES WITH EXPECTED PF USING REDUCED POPULATION VARIABILITY 82
FIGURE 6.17 CMPWL AND PAY FACTOR DISTRIBUTION FOR AQL PRODUCTION WITH REDUCED POPULATION VARIABILITY 83
FIGURE 6.18 CMPWL AND PAY FACTOR DISTRIBUTION FOR RQL PRODUCTION WITH REDUCED POPULATION VARIABILITY 84
FIGURE 6.19 DISTRIBUTION OF PASSING AC POPULATION AND THE TOLERANCES 85
FIGURE 6.20 DISTRIBUTION OF PASSING 0.075MM POPULATION AND THE TOLERANCES . 85
FIGURE 6.21 DISTRIBUTION OF PASSING 2.36MM POPULATION AND THE TOLERANCES ... 86
FIGURE 6.22 DISTRIBUTION OF PASSING 4.75MM POPULATION AND THE TOLERANCES ... 86
FIGURE 6.23 EP CURVES WITH EXPECTED PF USING POPULATION CHARACTERISTICS (GAP GRADED) 87
FIGURE 6.24 GAP GRADED CMPWL AND PAY FACTOR DISTRIBUTION FOR PRODUCTION AT AQL 89
FIGURE 6.25 GAP GRADED CMPWL AND PAY FACTOR DISTRIBUTION FOR RQL 90
FIGURE 6.26 DISTRIBUTION OF INDIVIDUAL GAP GRADED DENSITY VALUES 91
FIGURE 6.27 DISTRIBUTION OF INDIVIDUAL DENSE GRADED DENSITY VALUES 92
FIGURE 6.28 DISTRIBUTION OF LOT AVERAGES OF GAP GRADED DENSITY VALUES 92
FIGURE 6.29 DISTRIBUTION OF LOT AVERAGES OF DENSE GRADED DENSITY VALUES 93
FIGURE 6.30 DISTRIBUTION OF SIMULATED DENSITY DATA OF GAP GRADED MIXES 94
FIGURE 6.31 DISTRIBUTION OF SIMULATED DENSITY DATA OF DENSE GRADED MIXES .. 94
FIGURE 6.32 PAY FACTOR DISTRIBUTION OF DENSITY DATA OF GAP GRADED MIXES 95
FIGURE 6.33 PAY FACTOR DISTRIBUTION OF DENSITY OF DATA OF DENSE GRADED MIXES 95
FIGURE A1 FLOW CHART OF SIMULATION ANALYSIS 109
FIGURE C1 EP CURVES WITH EXPECTED PF USING POPULATION STANDARD DEVIATION AND C = 73 CMPWL (A=5%) 123
FIGURE C2 EP CURVES WITH EXPECTED PF USING POPULATION VARIABILITY STANDARD DEVIATION AND C = 63 CMPWL (A=1%) 124

FIGURE C3 EP CURVES WITH EXPECTED PF USING REDUCED POPULATION VARIABILITY AND C VALUE OF C= 73 CMPWL 125
FIGURE C4 EP CURVES WITH EXPECTED PF USING REDUCED POPULATION VARIABILITY AND C VALUE OF C= 63 CMPWL 126

LIST OF TABLES

TABLE 2.1 N_{DESJGN} VALUES FOR SUPERPAVE MIX DESIGN 17
TABLE 2.2 MARYLAND IN-PLACE DENSITY PAY FACTORS 20
TABLE 2.3 COMPARISONS OF GDOT AND CONTRACTOR QC TEST RESULTS USING MEANS 23
TABLE 2.4 COMPARISONS OF GDOT AND CONTRACTOR QC TEST RESULT USING VARIANCES 23
TABLE 2.5 COMPARISONS OF GDOT AND CONTRACTOR QC TEST RESULT USING PROJECT MEANS AND VARIANCES 24
TABLE 2.6 VARIABILITY VALUES USED IN INITIAL SCDOT HMA QA SPECIFICATION-REVISED SPEC 27
TABLE 2.7 SPECIFICATION LIMITS IN INITIAL AND REVISED SCDOT HMA QA SPECIFICATION 28
TABLE 2.8 CALCULATED AQL AND RQL BASED ON DIFFERENT SAMPLE SIZES 30
TABLE 2.9 PROBABILITIES THAT POPULATIONS WITH VARIOUS QUALITY LEVELS WOULD REQUIRE REMOVAL AND REPLACEMENT FOR ONE VERSUS FOUR INDEPENDENT QUALITY CHARACTERISTICS 32
TABLE 2.10 CORRELATION COEFFICIENTS FOR ALL PAIRS OF PLANT QUALITY CHARACTERISTICS 32
TABLE 2.11 EFFECTS OF CORRELATIONS BETWEEN VARIABLES USING SIMULATION ANALYSIS 33
TABLE 3.1 F AND *T* TEST ON RANDOM PROJECTS 35
TABLE 3.2 EXAMPLE OF F AND *T* TESTS BY MIX TYPE 36
TABLE 3.3 UNPAIRED ANALYSIS 37
TABLE 3.4 PAIRED ANALYSIS 38
TABLE 3.5 UNPAIRED ANALYSIS FOR HIGH POLISHED MIXTURES 39
TABLE 3.6 PAIRED ANALYSIS FOR HIGH POLISHED MIXTURES 39
TABLE 3.7 F AND *T* ANALYSIS ON DELTA FOR PROJECTS WITH UNIQUE TARGET VALUES – MIX HIGH POLISHED 42
TABLE 3.8 F AND *T* ANALYSIS ON DELTA FOR PROJECTS WITH UNIQUE TARGET VALUES – MIX GAP GRADE 42
TABLE 3.9 F AND *T* ANALYSIS ON DELTA FOR PROJECTS WITH UNIQUE TARGET VALUES – MIX S 42
TABLE 3.10 F AND *T* ANALYSIS ON DELTA FOR PROJECTS WITH UNIQUE TARGET VALUES – MIX RAP 43
TABLE 3.11 F AND *T* ANALYSIS ON DELTA FOR PROJECTS WITH UNIQUE TARGET VALUES – MIX VIRGIN 43
TABLE 4. 1 REPRESENTATIVE LOTS FOR THE 0.075, 2.36, 4.75, AND AC CONTENT OF GAP GRADED MIXTURES 48
TABLE 4.2 RISKS BASED ON AQL= 90% AND RQL = 40% FOR N=6. 51
TABLE 4.3 AQL AND RQL FOR *A= 1% AND B= 5% (*N=6). 51
TABLE 4.4 REVISED SPECIFICATION TOLERANCES FOR A= 1% AND B= 5%. 52
TABLE 5.1 CORRELATIONS BETWEEN MIX PARAMETERS FOR DENSE GRADED MIXTURES 53
TABLE 5.2 POPULATION CHARACTERISTICS 54
TABLE 5.3 EFFECTS OF CHANGE IN AC SPECIFICATION TOLERANCE 56
TABLE 5.4 EFFECTS OF CHANGE IN 0.075 SPECIFICATION TOLERANCE ON MF 58
TABLE 5.5 EFFECTS OF CHANGE IN 2.36 SPECIFICATION TOLERANCE ON MF 59
TABLE 5.6 EFFECTS OF CHANGE IN 4.75 SPECIFICATION TOLERANCE ON MF 60

TABLE 5.7 EFFECTS OF CHANGE IN AC SPECIFICATION TOLERANCE AND IMPACT ON MF 64
TABLE 5.8 EFFECTS OF CHANGE IN 0.075 SPECIFICATION TOLERANCE AND IMPACT ON MF 65
TABLE 5.9 EFFECTS OF CHANGE IN 2.36 SPECIFICATION TOLERANCE ON MF 66
TABLE 5.10 EFFECTS OF CHANGE IN 4.75 SPECIFICATION TOLERANCE ON MF 66
TABLE 6.1 STANDARD DEVIATION OF DIFFERENT PROPERTIES 77
TABLE 6.2 PROBABILITY OF RECEIVING ≥PF AT DIFFERENT CMPWL WITH POPULATION CHARACTERISTICS 77
TABLE 6.3 EXPECTED PAYMENT IN RELATION TO CMPWL WITH POPULATION CHARACTERISTICS* 78
TABLE 6.4 PROBABILITY OF RECEIVING ≥PF AT DIFFERENT PWL BY REDUCING POPULATION VARIABILITY 82
TABLE 6.5 STANDARD DEVIATION OF DIFFERENT PROPERTIES (GAP GRADED) 87
TABLE 6.6 PROB. OF RECEIVING ≥PF AT DIFFERENT CMPWL WITH POPULATION CHARACTERISTICS (GAP GRADED) 87
TABLE 6.7 AVERAGE PF IN RELATION TO CMPWL WITH POPULATION CHARACTERISTICS* (GAP GRADED) 88
TABLE 6.8 A AND B PARAMETERS FOR WEIBULL DISTRIBUTION OF HMA MIXTURES 93
TABLE 6.9 MODIFIED DENSE GRADED HMA MIXES PERCENT OF MAXIMUM DENSITY 96
TABLE A1 EXAMPLE OF EFFECT OF CORRELATION VALUE ON THE AVERAGE PF 118
TABLE B1 EFFECTS OF REDUCING POPULATION STANDARD DEVIATION 119
TABLE B2 EFFECTS OF INCREASING SPEC TOLERANCES 119
TABLE C1 WSDOT PAY FACTORS 121
TABLE C2 PROBABILITY OF RECEIVING ≥PF AT DIFFERENT CMPWL USING POPULATION CHARACTERISTICS & C = 73CMPWL (A=5%) 122
TABLE C3 PROBABILITY OF RECEIVING ≥PF AT DIFFERENT CMPWL USING POPULATION CHARACTERISTICS AND C = 63CMPWL (A=1%) 123
TABLE C4 PROBABILITY OF RECEIVING ≥PF AT DIFFERENT CMPWL BY REDUCING POPULATION VARIABILITY AND WITH C = 73CMPWL 125
TABLE C5 PROBABILITY OF RECEIVING ≥PF AT DIFFERENT CMPWL BY REDUCING POPULATION VARIABILITY AND WITH C = 63CMPWL 126

CHAPTER 1

1.1 Introduction

The Maryland State Highway Administration (MSHA) has implemented the Superpave mix design method since 1998. While the adoption of this mix design method has provided significant benefits to the state by improving rutting resistance of pavements, a reduction in asphalt cement content of the asphalt mixtures has been observed. These drier mixtures are more difficult to compact to target field density, especially in thin lifts. Lower density eventually leads to potholes, premature fatigue cracking and durability problems. The lower asphalt content of these mixtures reduces the asphalt film thickness, which accelerates oxidation and stripping effects. Other related problems include premature raveling at joints, increased segregation, and higher permeability.

Maryland SHA's concern with the lower asphalt levels in Superpave mixes have lead efforts through the HMA Pay Factor Team to explore strategies to increase the asphalt content in Superpave mixes. As a starting point, a national survey with other states was conducted. This initial survey and follow up national studies identified methods for adjusting binder content without compromising rutting performance of asphalt mixtures and remaining loyal to the Superpave philosophy. The applicability of these methods to MSHA conditions are addressed based on the findings of recent National Cooperative Highway Research Program projects, ongoing discussions with SHA engineers, and experts' feedback in this area (Objective I).

Another issue addressed in this study is the differences in HMA properties that have been observed over the years between samples taken at the plant versus behind the paver. A large set of SHA QA and QC data was analyzed statistically in the context of current specifications and pay factors to evaluate potential risks to both SHA and contractors (Objective II).

1.2 Research Approach

To address these objectives the following tasks and analysis were undertaken.

1.2.1 Increasing the Durability of Superpave Mixes

Maryland SHA has already explored strategies to increase the percentage asphalt in Superpave mixes[1] via a national survey with other states. In addition, there have been several major recent/ongoing national research projects related to the durability of Superpave mixes:

- NCHRP Project 9-09: Refinement of the Superpave Gyratory Compaction Procedure (Contractor: Auburn University/NCAT; completed)
- NCHRP Project 9-25: Requirements for Voids in Mineral Aggregate for Superpave Mixtures (Contractor: Applied Asphalt Technologies LLC; completed)
- NCHRP Project 9-31: Air Void Requirements for Superpave Mix Design (Contractor: Applied Asphalt Technologies LLC; competed)
- NCHRP Project 9-33: A Mix Design Manual for Hot Mix Asphalt (Contractor: Advanced Asphalt Technologies LLC; ongoing—mix design manual not yet published)

These national studies identified methods for adjusting binder content without compromising rutting performance of asphalt mixtures and without moving too far from the Superpave philosophy. In particular, the results from NCHRP Projects 9-25 and 9-31 as documented in NCHRP Report 567 *Volumetric Requirements for Superpave Mix Design* (2006) represent the best current thinking on enhancing durability of Superpave mixes.[2]

[1] Only Superpave dense-graded mixtures are considered here. Although Maryland places large quantities of SMA materials each year, these gap-graded mixtures do not conform to Superpave HMA mixture design criteria.
[2] R. Bonaquist, Advanced Asphalt Technologies LLC – personal communication

1.2.2 Review of QA/QC Data, Risk and Expected Pay Analysis

The research team first reviewed the state-of-practice in QA/ QC analysis by other states. An extensive literature review was conducted on HMA pay factors. The AASHTO and FHWA recommendations were examined as well. Specifically issues related to the following areas were examined:

- contractor vs. agency data,
- impact of sample size,
- evaluation and assessment of agency and contractor risks and use of OC curves, and,
- definition/evaluation of individual and composite pay factors.

A synthesis of key literature findings is provided in Chapter 2.

The analysis then proceeded with a review of the quality control (contractor) and quality acceptance (agency) data for HMA materials and an assessment of the risks and pay factor implications using the SHA data from 2002 to 2007. The effort of the HMA Pay Factor team in evaluating and assessing the existing method of acceptance and the pay factors for HMA materials described in SPS 504 and MSMT 735 was reviewed as well. Then an extensive analysis was performed to compare contractor and agency data at the plant and from the roadway ("behind the paver"). A series of statistical analyses (F and *t* tests) were conducted to assess and quantify the differences between these data sets. The research team then developed the Operating Characteristic (OC) curves based on the QA data and for estimating the risks to SHA and contractors (Type I and II risks). With the aid of a new simulation tool the associated pay factors

were analyzed using the population characteristics and considering potential correlations between the HMA mix parameters.

A series of meetings were scheduled with SHA engineers, the industry, and when appropriate with the HMA Pay Factor Team, to discuss the preliminary findings from the analyses and to formulate possible recommendations.

1.3 Organization of the Report

The first chapter presents the introduction, research objectives, the analysis approach and the organization of this report. Chapter 2 presents an extensive literature review on the durability of HMA mixtures and QA/QC and acceptance testing. Chapter 3 includes the results of the F and *t* test analyses comparing the Quality Assurance (QA) and Quality Control (QC) data. Chapter 4 presents the analyses related to the type I & II errors using the Operation Characteristic (OC) curves. Chapter 5 describes the simulation analysis used in this research for examining the percent within limits and mixture pay factor effects. Chapter 6 presents the pay factor analysis results for the HMA mix properties in-place density. Finally, chapter 7 includes the summary, conclusions, and recommendations.

CHAPTER 2 LITERATURE REVIEW

2.1 Improving Durability of Superpave HMA Mixtures

2.1.1 Durability Basics

The design of HMA mixtures requires balancing permanent deformation resistance, fatigue cracking resistance, strength, modulus, and other properties. The goal is to optimize the aggregate, asphalt, and mixture properties to produce the maximum pavement service life.

The durability of an HMA mixture is a measure of its resistance to disintegration-type distresses (e.g., raveling), moisture damage (e.g., stripping), and hardening over time (e.g., aging) with associated distresses (e.g., block cracking, top-down fatigue cracking). Such property can have a significant impact on asphalt concrete mixture performance and significantly change the other properties (e.g., permanent deformation and fatigue resistance) over time and thus it is normally considered in the mix design process by the control of asphalt content and air voids.

High mixture permeability is often associated with poor durability. Permeability is related to density, which in turn is related to the air voids in the compacted mix. A high air voids percentage allows water and air to penetrate the asphalt concrete mixture, causing stripping, moisture damage, and oxidation. These will eventually result in accelerated raveling and/or cracking. In addition, stripping and moisture damage significantly reduce the strength of the mix. The sizes of the voids, their interconnection, and the access of the voids to the surface of the pavement all have an influence on the permeability of the compacted HMA mixture. Asphalt film thickness, which is a function of asphalt content and aggregate gradation (particularly the fine portion), also has a major influence on potential moisture damage and durability.

Although increasing the effective asphalt binder content is the most direct method for increasing durability, other approaches that have been pursued either individually or in combination in recent years include:

- Changes to the design air voids (total voids in mix, VTM)
- Increasing minimum voids in mineral aggregate (VMA) requirements
- Imposing a maximum VMA cap
- Increasing the design voids filled with asphalt (VFA)
- Lower design compaction levels (N_{design}), including the "locking point" concept
- Increasing required field compaction levels (% density)

Many of these factors are interrelated, therefore their modification must be done with some care to avoid unintended consequences with regard to resistance to permanent deformations, fatigue cracking, and other structural distresses.

2.1.2 State of the Literature

NCHRP Project 9-25 "Requirements for Voids in Mineral Aggregate for Superpave Mixtures" and the closely related Project 9-35 "Air Void Requirements for Superpave Mix Design" examined the impacts of potential changes in the current criteria for design VTM, VMA, and VFA on the performance and durability of HMA. The research team for these studies conducted a thorough and critical literature review of the impact of variations in HMA volumetric properties on mixture performance and durability as the starting point for their studies. They then evaluated the effect of changes in VTM, VMA, VFA, aggregate specific surface, and other factors on the several performance measures of HMA.

These laboratory results, along with other data sets from the literature, were used to develop and validate a set of semi-empirical models for estimating quantitatively the structural performance (permanent deformation and fatigue cracking) and durability (via permeability and age hardening) of HMA mixtures as functions of HMA volumetric parameters. These comprehensive studies as summarized in NCHRP Report 567 (Christensen and Bonaquist, 2006) represent the best snapshot of the current state of the literature and the most rational interpretation of the state of practice on this subject.

The overall conclusion from these studies was that the current Superpave volumetric mix design criteria do not need major revision. However, the studies found that broadening the design air voids requirement to 3-5% is reasonable as long as the potential consequences on HMA performance are understood. In addition, while the study found it reasonable to consider changes in the minimum VMA or the addition of a maximum VMA limit, the effect of such changes, particularly if implemented in tandem with changes in design volumetrics requirements, must be carefully evaluated to avoid reducing resistance to permanent deformation and fatigue of the mix.

The following sections summarize the key findings from NCHRP Report 567 as related to mix durability. The material is reorganized here in order to focus more tightly on each of the major parameters available for improving durability.

Overall Findings

Superpave mixtures tend to be coarser, have lower binder contents, and be more difficult to compact in the field than earlier Marshall-based designs. The relatively few fines in combination with relatively high in-place air voids of Superpave mixtures can result in higher

permeability and more age hardening—i.e., less durability. Consequently, many state highway agencies have modified the requirements for VMA, VTM, and related factors for Superpave mixtures. The three most common Superpave modifications included: (1) an expansion of the design air voids from a target 4% to a range of 3% to 5% (i.e., matching the older Marshall mix design system); (2) addition of a maximum VMA limit at 1.5% to 2.0% above the minimum value; and (3) a slight increase in the minimum VMA values, typically by about 0.5%.

These modifications have been suggested individually, in combinations, or in addition to other changes (e.g., N_{design}). However, some care must be exercised. First, volumetric factors such as VBE, VTM, VMA, and VFA are all interrelated, making it difficult if not impossible to change only one volumetric parameter at a time. Second, changes in volumetric requirements, compaction levels, materials specifications, and other mixture characteristics are additive, and often in a nonlinear way. Unless these multiple types of interactions are carefully evaluated, they can cause significant and unanticipated reductions in pavement performance.

Binder Content

Fatigue resistance, which can be taken as a proxy for durability, is influenced by effective asphalt content (VBE) as well as design air voids, lab compaction (N_{design}), field compaction, and other factors. Christensen and Bonaquist found that each 1% increase in VBE corresponds to an increase in fatigue life of 13% to 15% (FIGURE 2.1).

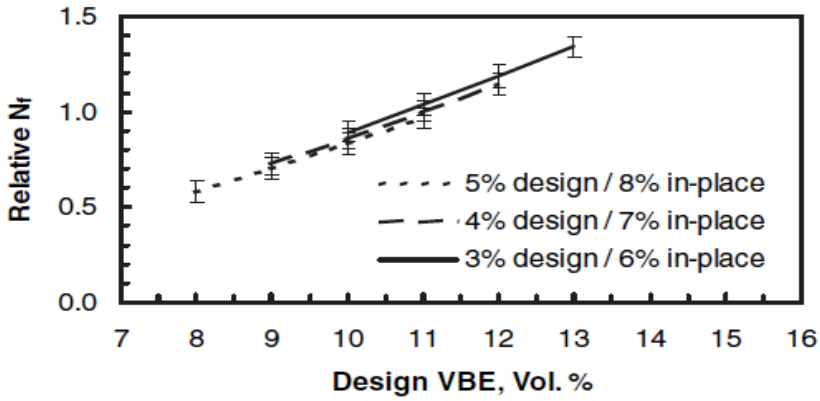

FIGURE 2.1 Effect of Design VBE on Relative In-Situ Fatigue Life (Christensen and Bonaquist, 2006)

Aggregate specific surface, a key quantity influencing binder film thickness and therefore mix durability, is very nearly proportional to the sum of the weight percent of material passing the 75, 150, and 300 μm sieves. This factor is defined as the fineness modulus 300 μm basis or FM_{300}. Christensen and Bonaquist found that FM_{300} is somewhat more effective in quantifying aggregate specific surface than using either the percent finer than 75 μm or the dust-to-binder ratio. Decreasing FM_{300} corresponds to increasing binder film thickness, which in turn should correspond to increased mix durability. However, Christensen and Bonaquist found that decreasing FM_{300} from 40 to 20 (a typical range for Superpave mixtures) at constant VMA had the detrimental side consequence of increasing rut rates by nearly a factor of 4 (FIGURE 2.2).

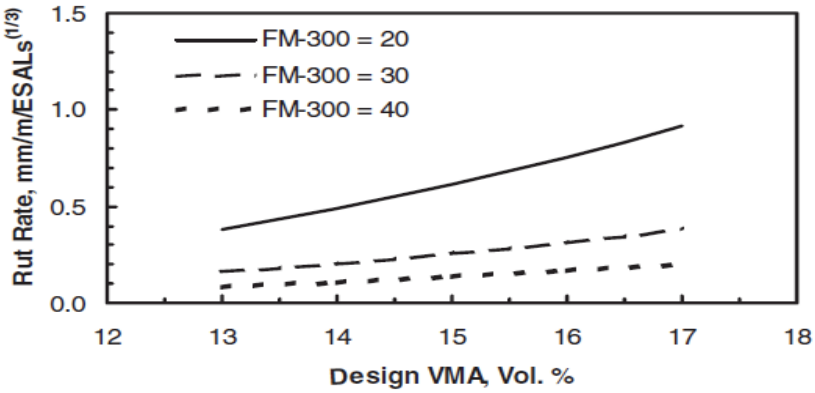

FIGURE 2.2 Effect of Aggregate Fineness and Design VMA on Rut Resistance of Superpave Mixtures at a Constant In-Place Air Void Content of 7% (Christensen and Bonaquist, 2006)

Design Air Voids

Decreasing design air voids while holding VMA constant increases VBE, which should result in increased fatigue resistance and durability. However, reducing VTM also reduces the field compaction effort required to achieve a given in-place air voids target; this would be expected to degrade both rutting resistance and fatigue resistance. As shown in FIGURE 2.3 and FIGURE 2.4, the latter effect dominates the response; decreasing design air voids while holding VMA and in-place air voids constant increases the rut rate and decreases the expected fatigue life.

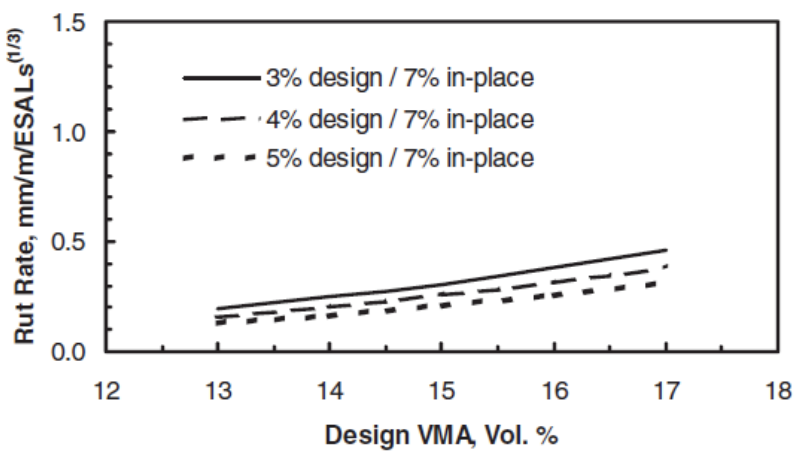

FIGURE 2.3 Effect of Design VMA and Air Voids on Rut Resistance of Superpave Mixtures at Constant In-Place Air Void Content (Christensen and Bonaquist, 2006)

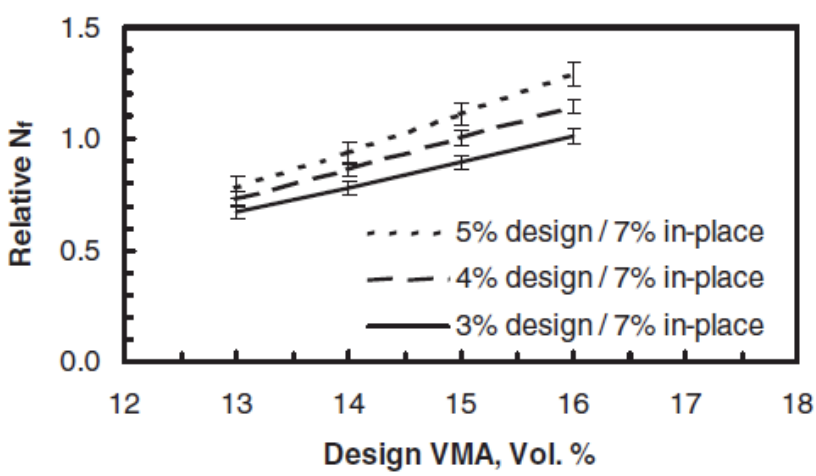

FIGURE 2.4. Effect of Design Air Voids and Design VMA on Relative In-Situ Fatigue Life at Constant In-Place Air Voids (Christensen and Bonaquist, 2006).

Note that decreasing the design air voids for a given aggregate structure at constant VMA has essentially the same effect as reducing the design compaction effort N_{design} (FIGURE 2.5; compare with FIGURE 2.3). Reducing design air voids or N_{design} at constant VMA simultaneously increases VBE (good for durability) and reduces the required field compaction effort for fixed target density (bad for durability). The latter effect generally dominates and will tend to decrease permanent deformation resistance, fatigue resistance, and durability. Conversely, increasing design air voids (or N_{design}) will increase the difficulty of field compaction. This may increase in-place air voids which in turn may counteract any benefits from increased design air voids as well as result in a more permeable mix that is more susceptible to age hardening and moisture damage.

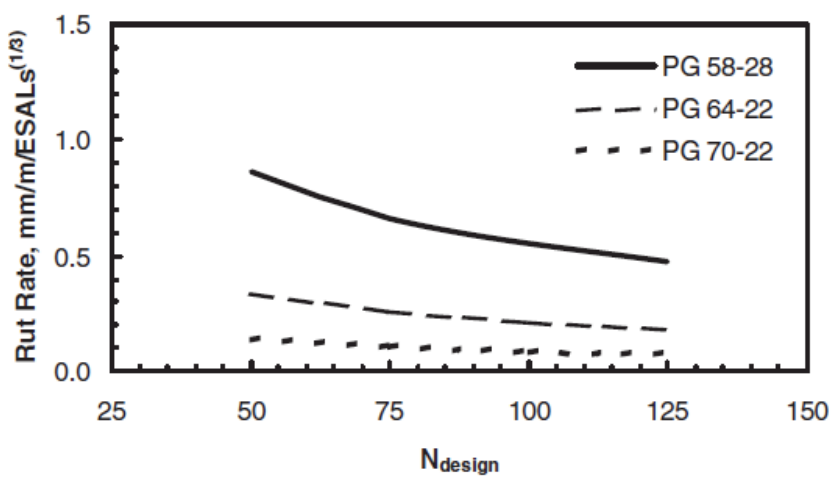

FIGURE 2.5 Effect of Binder Grade and N_{design} on Rut Resistance at 4% Design Air Voids and 7% In-Place Air Voids (Christensen and Bonaquist , 2006)

In-Place Air Voids

Christensen and Bonaquist found from their empirical performance models that a 1% decrease in in-place air void content at constant design air voids increases both rut resistance and

fatigue resistance by about 20% (FIGURE 2.6 and FIGURE 2.7). Decreasing design air voids while simultaneously decreasing in-place air voids provides even greater benefits in terms of rut and fatigue resistance and mix durability (e.g., FIGURE 2.7). This is consistent with the very rough "rule of thumb" by Linden *et al.* (1988) that every 1% increase in in-place air voids results in about a 10% reduction in performance. Achieving adequate compaction in the field is clearly the best thing to do for pavement performance, including durability.

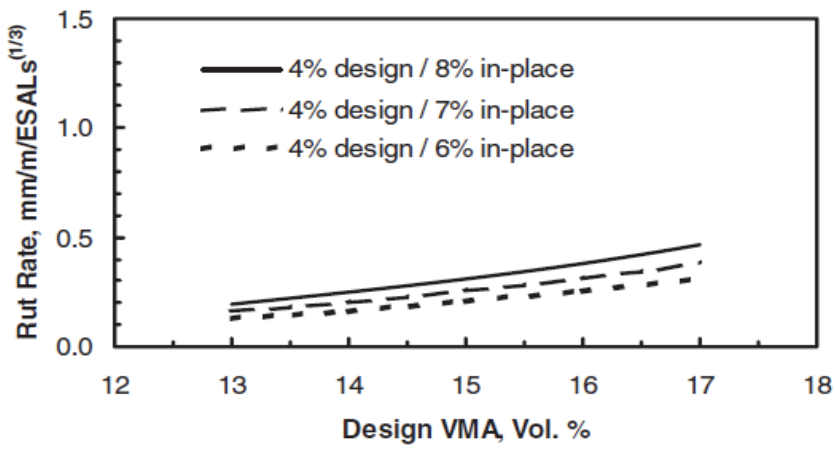

FIGURE 2.6 Effect of VMA and In-Place Air Voids on Rut Resistance of Superpave Mixtures at Constant Design Air Void Content (Christensen and Bonaquist, 2006)

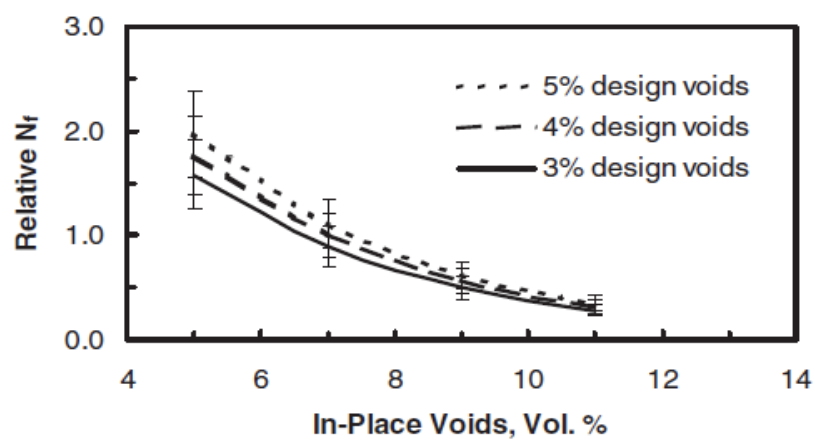

FIGURE 2.7 Effect of In-Place Air Voids and Design Air Voids on Relative In-Situ Fatigue Life (Christensen and Bonaquist, 2006)

Before modifying Superpave mix design specifications, the level of in-place density being achieved in projects should be critically examined. Inadequate field compaction will have a broad and significant negative impact on pavement performance that can only be partially offset by altered mix design. Simultaneously decreasing design air voids and in-place air voids by a similar amount will increase rut resistance and fatigue and decrease permeability — therefore provide a more durable and better performing pavement.

VMA

Increasing VMA, while maintaining constant design air voids increases VBE and therefore improves fatigue resistance and, by implication, durability (FIGURE 2.4). However, Christensen and Bonaquist found that a 1% increase in VMA at constant design air voids decreases rutting resistance by about 20% (FIGURE 2.6) unless care is taken to ensure that adequate aggregate specific surface is maintained.

Permeability

Permeability is an inverse indicator for durability--i.e., durability tends to decrease with increasing permeability. Permeability increases with increasing air voids (FIGURE 2.8) and decreasing aggregate specific surface (i.e., increasing aggregate size). Permeability can be modeled effectively using the concept of effective air voids, defined as the total air voids minus the air void content at zero permeability. At constant total air voids effective air voids decrease with increasing aggregate fineness. Based on permeability study data by Choubane *et al.* (1998) and others, permeability increases by about 10^{-3} cm/s for every 1% increase in air voids or 3% decrease in FM_{300} (FIGURE 2.8).

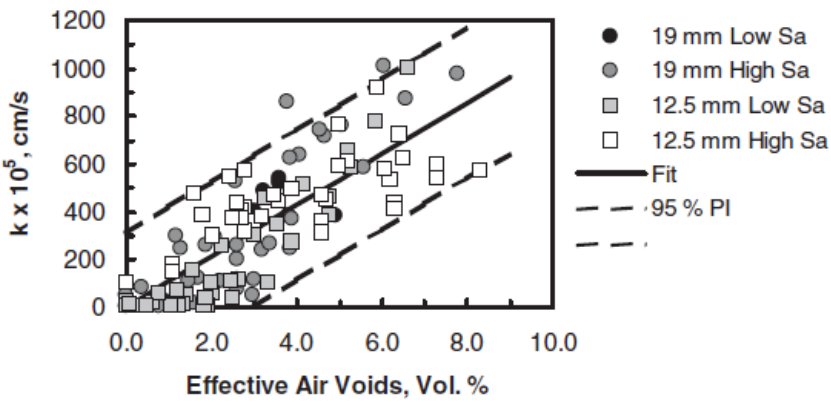

FIGURE 2.8 Permeability of Specimens from Choubane *et al.* (1998) and NCHRP Projects 9-25 and 9-31 as a Function of Effective Air Void Content (Christensen and Bonaquist, 2006)

Permeability of HMA measured from laboratory-prepared specimens tends to be significantly lower than permeability values measured on field cores of the same mixture. Consequently, laboratory measurement of mixture permeability has little utility for use in routine mix designs.

Age Hardening

Age hardening of HMA is a key factor in durability; increased hardening tends to produce durability problems associated with raveling, block cracking, and top-down fatigue cracking. Christensen and Bonquist found that hardening depended not only on air void content but also on the specific combination of aggregate and binder in the mixture. Applying a modified version of the Mirza and Witczak (1995) global aging system at a mean annual air temperature of 15.6^{o}C, Christensen and Bonaquist found that the age hardening ratio for the mixture decreased about 2% to 7% for every 1% increase in FM_{300} (i.e., decreasing aggregate size) and increased about 5% to 14% for every 1% increase in in-place air voids (FIGURE 2.9). In general, the effect of increasing air voids by 2% on age hardening is comparable to the effect of decreasing FM_{300}

by 5%. Careful control of aggregate specific surface can therefore help maintain good resistance to age hardening.

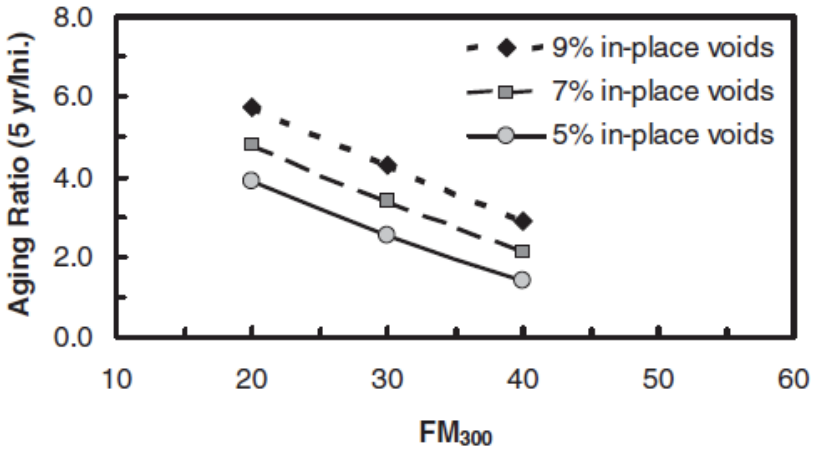

FIGURE 2.9 Predicted Mixture Age-Hardening Ratio at 25°C and 10 Hz as a Function of In-Place Air Void Content and FM_{300} for a MAAT of 15.6°C (Christensen and Bonaquist, 2006)

Summary

The very extensive analyses summarized by Christensen and Bonaquist in NCHRP Report 567 show that optimal performance for HMA mixtures can be ensured by: (1) including enough asphalt binder to ensure good fatigue resistance (and, by implication, durability); (2) assuring adequate mineral filler and fine aggregate to keep permeability low (good for durability) and rut resistance high; and (3) obtaining proper compaction in the field (also good for durability). The results also clearly demonstrate the interdependence of many of the volumetric variables in a mix design. It is difficult if not impossible to change one volumetric parameter (e.g., design air voids) without simultaneously changing several others (e.g., VBE, VMA, or in-place air voids at a given compaction effort). The effects of these factors are additive, and often in a nonlinear way. Individual factors that may not produce any serious decrease in performance may in combination with other simultaneous changes cause premature

failure. This must be kept in mind during any attempts to modify current requirements for volumetric composition of HMA mixtures.

With specific regard to durability, Christensen and Bonaquist cite four critical factors for improvement while simultaneously maintaining good rut resistance:

1. Effective binder content should be increased to provide better fatigue resistance.
2. Aggregate fineness should be increased to decrease mixture permeability.
3. Design air voids can be decreased to improve compaction, but only if in-place air void targets are also significantly decreased.
4. Targets for in-place air voids can be decreased.

2.1.3 Implications for Maryland SHA Practice

In July 2008, while the present research project was already underway, Maryland SHA adopted a new volumetric mix design specification (Section 904) in an effort to improve durability.[3] The sole change in the specification was a reduction in the N_{design} values. The new Maryland SHA values are summarized in TABLE 2.1, along with the national standards as specified in AASHTO M323. The new Maryland specification reduces N_{design} by 10 gyrations for design level 2, 20 gyrations for design levels 3 and and 4, and 25 gyrations for design level 5 relative to the AASHTO national specification values.

TABLE 2.1 N_{design} Values for Superpave Mix Design

Design Level	20-Year Design Traffic (Million ESALs)	AASHTO M323 N_{design}	MD SHA 904 N_{design}
1	<0.3	50	50
2	0.3 to <3	75	65
3	3 to <10	100 (75)*	80
4	10 to <30	100	80
5	≥30	125	100

*When the estimated 20-year design traffic loading is between 3 and < 10 million ESALs, the agency may, at its discretion, specify N_{design} = 75

The expected ramifications of this specification change can be best summarized by quoting directly from NCHRP Report 567:

[3] This new specification had been publicized in draft form before it was formally implemented in July 2008.

"Some engineers may suggest that simply lowering N_{design} will provide significant improvement in durability, believing that this will increase design binder content and improve field compaction, resulting in improved fatigue resistance and lowered permeability. However, lowering N_{design} will not necessarily increase design binder content—in this situation, many producers will adjust their aggregate gradation so that the design binder content remains as low as possible since this will minimize the cost of the HMA and maximize profits. Paying for asphalt binder as a separate item removes the incentive to minimize binder content, but in no way guarantees that binder contents will be sufficient for good fatigue resistance. If an agency believes that current minimum binder contents are too low for adequate fatigue resistance and/or durability, the most effective and efficient remedy is simply to increase these minimum values. A similar situation exists for field compaction. Lowering N_{design} values will tend to make HMA mixtures easier to compact, but will not guarantee that in-place air voids will decrease. Assuming most successful contractors are motivated not by maximizing losses but by maximizing profits (and therefore staying in business), the competitive marketplace demands that they adjust their compaction methods to optimize their profits, based on the cost of performing compaction and the penalties and/or bonuses that results from different levels of compaction. Lowering N_{design} will help improve field compaction, but unless this is combined with a payment schedule adjusted to produce additional incentive for thorough field compaction, in the long run it will not likely result in significant lowering of in-place air voids." (Christensen and Bonaquist, 2006).

In other words, a simple reduction in N_{design} is not necessarily the most effective way of achieving increased mix durability as producers can “game” the system to keep binder contents low. Nonetheless, the new specification has been in place for nearly a year. Although the true measure of its effectiveness will be mixture durability, rutting, and fatigue performance over a period of many years, there are some actions that Maryland SHA can implement now to determine whether the specification change is having the intended effects. These include:

1. Comparison of QA binder content data for mixtures designed before and after the specification change to see whether the asphalt percentage has increased on average as intended.
2. Comparison of QA in-place density data for mixtures designed before and after the specification change to see whether lower in-place air voids are now being achieved.
3. Review density pay factor schedules to ensure that there is sufficient incentive for contractors to achieve lower in-place air voids.

With regard to point 3 above, Maryland SHA also revised its in-place density pay factor specification (Section 504) in July 2008. The old and new pay factor schedules are compared. The new in-place density pay factors are slightly higher than the old and should provide some incentive for contractors to reduce in-place air voids.

TABLE 2.2 Maryland In-Place Density Pay Factors

Lot Average % Minimum	No Individual Sublot Below %	Old Pay Factor % (Pre-July 2008)	New Pay Factor % (Post-July 2008)
94.0	94.0	105	105.0
93.8	93.7	103	104.5
93.6	93.4	103	104.0
93.4	93.1	103	103.5
93.2	92.8	102	103.0
93.0	92.5	102	102.5
92.8	92.2	101	102.0
92.6	91.9	100	101.5
92.4	91.6	100	101.0
92.2	91.3	100	100.5
92.0	91.0	100	100.0
91.8	90.8	95	99.0
91.6	90.6	95	98.0
91.4	90.4	95	97.0
91.2	90.2	95	96.0
91.0	90.0	95	95.0
90.8	89.8	85	94.0
90.6	89.6	85	93.0
90.4	89.4	85	92.0
90.2	89.2	85	91.0
90.0	89.0	85	90.0
89.8	88.8	75	89.0
89.6	88.6	75	88.0
89.4	88.4	75	87.0
89.2	88.2	75	86.0
89.0	88.0	75	85.0
88.8	87.8	--	84.0
88.6	87.6	--	83.0
88.4	87.4	--	82.0
88.2	87.2	--	81.0
88.0	87.0	--	80.0
Less than 88.0	87.0	--	75.0 or rejected by Engineer

2.2 Quality Measures for HMA Mixtures

2.2.1 Introduction

Over the years different agencies have implemented different quality measures in order to increase the quality of hot-mix asphalt (Parker and Turochy 2007). Thus, several methods have been developed for measuring the level of quality (Burati and Weed 2006). After determining the quality indicator and the quality characteristics that need to be measured, a tolerance is specified for each measured characteristic (Sholar et al. 2005). In this process it is also important to evaluate the risks involved with the specifications to make sure that the specs provide acceptable levels of risks for the agency and contractor (Mahoney and Muench 2001).

The objective of the literature review was to review these past experiences on the development of specifications by different state DOTs and focus on the following important aspects: comparison of QA and QC data; definition of quality indicators; establishment of specification tolerances; and risk analysis.

2.2.2 Comparison of QA and QC data (F and *t* test)

Many projects have investigated the null hypothesis - that the contractor-performed tests (plant QC data) provide the same results as state DOT test (behind the paver QA data in the case of MSHA) - for use in the acceptance decisions (Parker and Turochy 2007). Some examples of the most relevant studies are reported next.

Parker and Turochy (2007) investigated whether or not the contractor and state DOT results are from the sample populations. The studied states included: Georgia, Florida, North Carolina, Kansas, California, and New Mexico. The study found that the differences in means

and variances between the contractor and state DOT are often significant. Generally, the DOT data had more variability in comparison to contractor's data. The conclusion is that the contractor and the agency's data are not from the same population.

Turochy et al. (2006) investigated the comparison of contractor quality control and Georgia DOT data. The analyzed data were from the 2003 construction season. The target value of each job-mix formula (JMF) was used to calculate the difference between an observed test value and the target values. The following variables were used in the analysis:

$$\Delta_{GDOT}=X_{GDOT}-X_{JMF} \qquad \textbf{EQUATION 2.1}$$

$$\Delta_{CONT}=X_{CONT}-X_{JMF} \qquad \textbf{EQUATION 2.2}$$

The mean and variance of these values were calculated for both data sets and then compared using paired F-test and *t*-test respectively. The data were analyzed in two different ways: (1) analysis of data across all projects; and (2) on a project-by-project bases. The results were as follows:

1- Analysis of data across all projects

The first round of analysis was done across all HMA placements in the 2003 construction season to determine the extent of differences between contractor-performed testing and that of GDOT. These results are summarized in Table 2.3.

The p-values represent the extent to which the difference in average is significant. As the p-value increases the significance of difference decreases. The last column in Table 2.4 illustrates whether or not the property is used in the payment equation. Among the four sieves used for the pay equation the differences are significant for three of them (% passing on 1/2", 3/8", and #8).

The same comparison was done on the variances of GDOT and the contractor data using the F-test. The results are summarized in Table 2.4.

TABLE 2.3 Comparisons of GDOT and Contractor QC Test Results Using Means (Turochy et al. 2006)

Property	n	$\bar{\Delta}_{GDOT}$, %	$\bar{\Delta}_{CONT}$, %	Difference	p-Value	Pay
% pass 1″	395	0.258	0.295	NSD	0.462	NO
% pass ¾″	791	0.398	0.469	NSD	0.166	NO
% pass ½″	1067	0.314	0.118	SD	0.002	YES
% pass ⅜″	953	0.516	0.329	SD	0.005	YES
% pass #4	402	0.506	0.392	NSD	0.128	YES
% pass #8	1142	0.449	0.244	SD	<0.001	YES
% pass #50	282	0.897	0.763	NSD	0.094	NO
% pass #200	1141	0.334	0.447	SD	<0.001	NO
% asphalt	1135	0.005	0.002	NSD	0.634	YES

TABLE 2.4 Comparisons of GDOT and Contractor QC Test Result Using Variances (Turochy et al. 2006)

Property	n	S^2_{GDOT}, %	S^2_{CONT}, %	Difference	p-Value	Pay
% pass 1″	395	1.527	1.363	NSD	0.131	NO
% pass ¾″	791	4.410	3.831	NSD	0.024	NO
% pass ½″	1067	9.343	6.576	SD	<0.001	YES
% pass ⅜″	953	8.479	5.545	SD	<0.001	YES
% pass #4	402	9.450	8.606	NSD	0.175	YES
% pass #8	1142	8.673	6.561	SD	<0.001	YES
% pass #50	282	3.971	4.004	NSD	0.472	NO
% pass #200	1141	1.137	0.791	SD	<0.001	NO
% asphalt	1135	0.088	0.045	SD	<0.001	YES

2- Analysis of data on project-by-project bases.

In this set of analysis were included only projects for which at least six GDOT comparison tests were recorded. These analyses were performed on the asphalt content, percent passing the ½ in sieve, and percent passing the No. 200 sieve. The results on both means and variances are summarized in Table 2.5. As a general trend, the differences in variances tend to be higher than the difference in the means. In conclusion, the analysis of GDOT QA and QC data for HMA shows that differences in results of tests conducted by GDOT and the contractors differ often significantly

TABLE 2.5 Comparisons of GDOT and Contractor QC Test Result Using Project Means and Variances (Turochy et al. 2006)

Property	Projects	Projects with Larger GDOT Means	Projects with Significant Differences	Projects with Significantly Larger GDOT Means	Projects with Larger GDOT Variances	Projects with Significant Differences	Projects with Significantly Larger GDOT Variances
% asphalt	41	27 (66%)	1 (2%)	0	35 (85%)	1 (2%)	1 (2%)
% pass ½″	34	15 (44%)	0	0	20 (59%)	2 (6%)	2 (6%)
% pass #200	45	21 (47%)	2 (4%)	2 (4%)	34 (76%)	3 (7%)	3 (7%)

2.2.3 Quality Indicators

Several studies have examined the use of alternative quality indicators for HMA mixtures (Burati and Weed 2006). Some examples of the most relevant studies are reported next.

Burati and Weed (2006) investigated the accuracy and precision of typical quality measures (PWL, AAD and CI). From the statistical point of view an accurate 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:

a) Percent Within Limits (PWL)

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

$$Q_L = \frac{X - LSL}{s} \qquad \textbf{EQUATION 2.3}$$

and

$$Q_U = \frac{USL - X}{s} \qquad \textbf{EQUATION 2.4}$$

Where:

Q_L = quality index for the lower spec limit

Q_U= 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 ($PWL_T = PWL_U + PWL_L - 100$).

Where:

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

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

PWL_T=percent within the upper and lower specification limits

As seen in the equations, this process takes both the mean and standard deviation into account.

b) Average Absolute Deviation (AAD)

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

$$AAD = \frac{\sum |X_i - T|}{n} \qquad \textbf{EQUATION 2.5}$$

Where:

Xi = individual test results

T = target value

n = number of tests per lot

c) 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.

$$CI=\sqrt{\frac{\sum(X_i-T)^2}{n}} \qquad \textbf{EQUATION 2.6}$$

For each of the three measures, 10,000 lots were generated. The results illustrated that as the number of samples increases (3 to 5 to 10) the variability between the generated lot and actual population decreases. The study also showed that for PWL, the variability increased as the actual population PWL moves from 0 or 100 PWL and peaked at 50 for both the CI and AAD the variability increased as the actual population vales moved from 0. The average differences of simulated lots and actual population values indicated that both the AAD and PWL are unbiased whereas CI is a biased estimator.

2.2.4 Evaluating Specification Limits

Several studies have investigated the definition and adequacy of specification limits (Burati 2006, Sholar et al. 2005). Burati (2006) investigated the accuracy of assumed standard deviations by South Carolina Department of Transportation (SCDOT) when developing their

initial QA specifications. The SCDOT QA specification is based on lot-by-lot acceptance, therefore it is appropriate to use a variability of a typical lot. In order to achieve this, the standard deviation values for each lot must be calculated and then be pooled to get a typical within-lot standard deviation. In addition to the within-lot variability, the agency should also consider the typical *process* variability. Based on multiple reports and specially the *Optimal Procedures for Quality Assurance Specifications* (FHWA-RD-02-095) there is no single correct way to decide the typical variability. Burati suggested to add both variances (within-lot and process variability), and take the square root of that value to obtain the typical standard deviation. Table 2.6 summarizes the assumed standard deviations for the current spec and the standard deviations found by Burati.

TABLE 2.6 Variability Values Used in Initial SCDOT HMA QA Specification-Revised Spec (Burati 2006)

Acceptance Quality Characteristic	Standard Deviation Assumed in Initial PWL Specification	Standard Deviation Selected for Revised QA Specification
Asphalt content		
Surface	0.25	0.22
Intermediate	0.29	0.26
Air voids	0.76	0.70
VMA	0.76	0.70
Density	1.21	1.09

After defining the typical variability, the number of standard deviations that the population should fall within the population mean is calculated. Since the AQL is 90% for SCDOT this value comes out to be 1.645. The following table summarizes the current specification and the suggested specification limits.

TABLE 2.7 Specification Limits in Initial and Revised SCDOT HMA QA Specification (Burati 2006)

Acceptance Quality Characteristic	Initial Specification Limits, %	Derivation of Tolerance (1.645σ)	New Specification Limits, %
AC			
Surface	JMF ± 0.41	1.645 × 0.22 = 0.36	JMF ± 0.36
Intermediate	JMF ± 0.48	1.645 × 0.26 = 0.43	JMF ± 0.43
AV	JMF ± 1.25	1.645 × 0.70 = 1.15	JMF ± 1.15
VMA	JMF ± 1.25	1.645 × 0.70 = 1.15	JMF ± 1.15
Density	92–96	1.645 × 1.09 = 1.80	92.2–96.0

For all four parameters (Asphalt Content, Air Voids, Voids in Mineral Aggregate, and Density) the suggested limits are narrower. The results of this study confirm the importance of the continuous monitoring of the specifications adequacy and the need for adjustments based on the test results obtained from actual projects.

2.2.5 Risk Analysis and Pay Factor Evaluation

There are generally two types of acceptance plans: 1) The accept/reject acceptance plans and 2) Acceptance plans that include pay adjustment provisions (FHWA-RD-02-095). These methods are presented next using specific studies from the literature.

2.2.5.1 Accept/Reject Acceptance Plans

Villiers et al. (2003) evaluated the PWL specification parameters. The study illustrated how to balance the seller and buyer's risk by adjusting certain specification parameters. In this process the following parameters are defined:

a) Buyer's risk (β): The probability that the buyer would accept poor quality material
b) Rejectable Quality Level (RQL): The maximum level of quality that the material is fully unacceptable

c) Seller's risk (α): The probability that seller's good quality material would be rejected

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

The AQL and RQL are the parameters that agency can utilize to determine incentives and penalties. Each state sets its own AQL and RQL and for the state of Florida these values are set at 90% and 50% respectively.

Using the Operation Characteristic Curve (OC Curve), the study illustrated that with the current spec limits and sampling size of 4 or 5 per lot the buyer's risk was equal to 33 and 24% respectively, figure 2.1. In order to achieve the AASHTO recommended risk level of 5%, ten samples per lot were required. Since this number of sampling is not practical, it was required to adjust the 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 need to change their AQL and RQL. Table 2.8 summarizes these values.

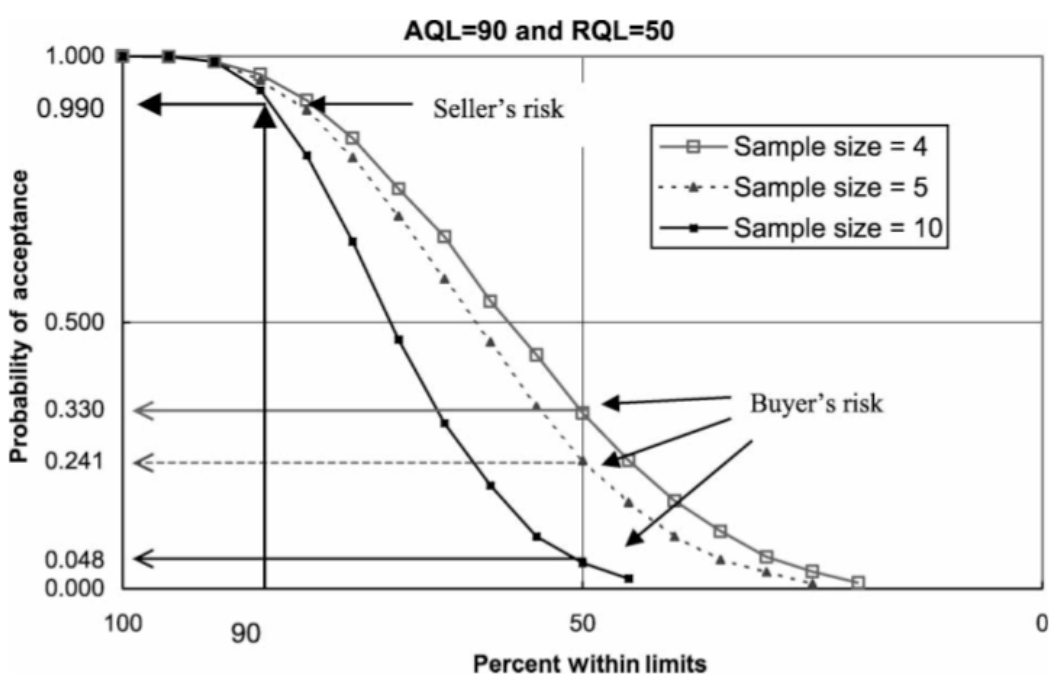

FIGURE 2.10 Contactor and Owner Risk using Unknown Standard Deviation (Villiers et al. 2003)

TABLE 2.8 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 needs to either increase sampling size or adjust the AQL and RQL values to achieve the recommended risk levels.

2.2.5.2 Acceptance Plans that Include Pay Adjustment Provisions

In order to consider the impact of specification on provisions, simulation analysis has been used to generate alternative scenarios based on the population characteristics observed from the HMA production (Burati 2005, Mahoney and Muench 2001). For example, a study by Burati (2005) used computer simulation to illustrate how the removal and replacement provisions place much greater risk on the contractor. In addition, 1742 sets of test results were analyzed for correlations.

Many state highway agencies (SHAs) use the recommended pay factor relationship recommended by the *AASHTO Quality Assurance Guide Specification (*1996) which is:

$$PF = 55 + (0.5 * PWL) \qquad \textbf{EQUATION 2.7}$$

From this equation it can be seen that the maximum pay factor is 105% when PWL = 100 and the minimum pay factor is 55% when PWL = 0. However, almost all states reject any lot that has a PWL smaller than RQL and some states have some form of remove and replace provisions

(Burati 2005). Some agencies use as many as four or more quality characteristics to determine the final pay factor for the lot. The study by Burati used the common method of weighted average of the individual pay factors to determine the composite pay factor. 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.

One problem that is caused by the remove and replace provision is how often the lot is actually an acceptable one but it gets rejected. Table 2.9 clearly illustrates how going from one quality characteristic pay factor to four HMA mix characteristics increases the probability of rejecting a good quality material. For example, at 90 PWL and three samples per lot (n=3) the probability of rejecting a lot is 6% for a one mix characteristic; the probability rises to 22% for a four mix property pay factor. This table clearly illustrates that the remove and replace provision is problematic.

The composite pay factor that SCDOT uses to calculate the composite pay factor is:

$$LPF = 0.25(PF_{AC}) + 0.30(PF_{AV}) + 0.10(PF_{VMA}) + 0.35(PF_{DEN})$$ **EQUATION 2.8**

This equation assumes that the four parameters are statistically independent. To investigate any possible correlations between the mixture parameters project test results were analyzed. Only the correlations of the following pairs were analyzed: AC-AV, AC-VMA, and AV-VMA.

TABLE 2.9 Probabilities that Populations with Various Quality Levels Would Require Removal and Replacement for One Versus Four Independent Quality Characteristics (Burati 2005)

Population PWL	One QC[a] $n = 3$	One QC[a] $n = 4$	One QC[a] $n = 5$	Four QC[b] $n = 3$	Four QC[b] $n = 4$	Four QC[b] $n = 5$
100	0.000	0.000	0.000	0.000	0.000	0.000
95	0.014	0.006	0.001	0.055	0.024	0.004
90	0.060	0.032	0.007	0.219	0.122	0.028
85	0.107	0.085	0.045	0.364	0.299	0.168
80	0.184	0.120	0.114	0.557	0.400	0.384
75	0.313	0.226	0.187	0.777	0.641	0.563
70	0.363	0.321	0.288	0.835	0.787	0.743
65	0.486	0.434	0.422	0.930	0.897	0.888
60	0.570	0.557	0.552	0.966	0.961	0.960
55	0.630	0.666	0.679	0.981	0.988	0.989
50	0.727	0.725	0.768	0.994	0.994	0.997
45	0.789	0.817	0.864	0.998	0.999	1.000
40	0.847	0.866	0.906	0.999	1.000	1.000
35	0.898	0.934	0.952	1.000	1.000	1.000
30	0.938	0.945	0.969	1.000	1.000	1.000
25	0.964	0.979	0.990	1.000	1.000	1.000
20	0.977	0.988	1.000	1.000	1.000	1.000
15	0.992	1.000	1.000	1.000	1.000	1.000
10	1.000	1.000	1.000	1.000	1.000	1.000
5	1.000	1.000	1.000	1.000	1.000	1.000
0	1.000	1.000	1.000	1.000	1.000	1.000

[a]With one quality characteristic.
[b]With four independent quality characteristics.

The correlation values are summarized in Table 2.10.

TABLE 2.10 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 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 2.11 illustrates these effects.

TABLE 2.11 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.

CHAPTER 3 COMPARISON OF MARYLAND QA & QC DATA

Several state specifications have used QA (Quality Assurance- behind the paver) and QC (Quality Control- at the plant) data in their acceptance plans. The Maryland HMA Pay Factor Team has been discussing such option as related to the past and current SHA specifications for the acceptance of the Superpave HMA mixtures. This comparison involves the use of F and t tests to determine whether QA and QC data can be considered as statistically representing the same population, in statistical terms. Standard statistical analyses (F and *t* test) were conducted comparing the QA and QC data for all the HMA mixtures (aggregate level), as well as for specific mixtures (disaggregating the data into subsets representing common mixture types and characteristics). The steps of the analysis are described in the following sections along with the results. All the analyses followed the steps indentified in the SHA MSMT 733 report of the State Highway Administration.

3.1 F and *t* Tests

3.1.1 Initial Exploratory Assessment Using Random Projects

An initial comparison between the QA and QC data was conducted using 15 randomly selected projects: 5 large, 5 medium, and 5 small size projects. To assess the null hypothesis (i.e., equal mean and the standard deviation for the two populations, QA and QC), the F and *t* tests were performed on all mix properties together and at 5% level of significance. The results, shown in Table 3.1, indicated that as the number of observations (n) increased, the rejection rate increased. Thus, the data and comparison had to be analyzed further.

TABLE 3.1 F and *t* Test on Random Projects

	Small Sample Size		Medium Sample Size		Large Sample Size	
	t Tests	F Test	t Tests	F Test	t Tests	F Test
Accepted	100%	83%	88%	75%	50%	45%
Rejected	0%	17%	13%	25%	50%	55%

3.1.2 Analysis Based on Mixture Type and Property (Unmatched Lots and Sublots)

Each project is identified with a series of numbers and letters which is called the Job Mix Formula ID (JMFID). The JMFID of each project describes the following characteristics of that project:

i) Region

ii) Plant Number (The number identification of the plant)

iii) Nominal Maximum Aggregate Size (4.75mm, 9.5mm, 12.5mm, 19mm, 25mm, and 37.5mm)

iv) Mix Type (Virgin (V), Rap (R), Trinidad Lake Asphalt (TLA), Glass (GL), Gap Grade (G), and High Polish (H))

v) ESAL Level

vi) Binder Type (A, B, C, D, E, and F)

vii) Mix Number (01 to 99)

viii) Status (Tentative and Final)

For example a JMFID of N12312V2A01T means that the job is in the North region (N), the plant number is 123, the mix band is 12.5 mm, mix type is Virgin, ESAL level is 2, binder type is 58-22 (A), mix number is 01, and the status is tentative (T).

Four QA properties are used by Maryland SHA (2008 specification) for determining mixture pay factors:

i) Aggregate Passing 0.075mm /No. 200 sieve

ii) Aggregate Passing 2.36mm / No. 8 sieve

iii) Aggregate Passing 4.75mm / No. 4 sieve

iv) Asphalt Content (AC)

In order to sort the QA and QC data conveniently by mix type and mix characteristics it was necessary to break the JMFIDs into their components (Mix Type, Max Aggregate Size (Mix band), mix property, etc.). After parsing the JMFIDs, the F and *t* analyses were conducted by mix type and property (e.g. G-12-AC, H-12- AC, etc.) at the 5% level of significance. An example of these analyses is shown in Table 3.2. In many cases the Ho hypothesis was rejected. Overall, only 53% of the t tests and 21% of the F tests were "Accepted". This comparison dealt with unpaired observations (i.e., different number of observations for QA and QC data). Due to the low level of acceptance, it was necessary to disaggregate the data into more details.

TABLE 3.2 Example of F and *t* Tests by Mix Type

MixSize	MixType	Property	t Test	F Test	# of Observations		Mean		Variance	
					QA	QC	QA	QC	QA	QC
12	G	AC	Rejected	Rejected	636	870	6.4074	6.5140	0.0881	0.0261
12	H	AC	Rejected	Rejected	311	429	4.9040	4.8390	0.0941	0.0486

3.1.3 Analysis Based on Mixtures Type and Property (Matched Lots and Sublots)

Since for the 12-G-AC and 12-H-AC mixtures, shown in Table 3.2, both the F and *t* tests were rejected, these data were further examined. In the next step the F and *t* analysis were run by matching the lots and sub-lots of the QA and QC data for each project. Very often such task has been shown to be challenging since there is not a unique reciprocity between the numbering of lots and sublots between the QA and QC data, and the recoding dates did not match. Thus, while such analysis has shown to increase the acceptance rate, it was felt that the analysis were unreliable.

3.1.4 Unpaired vs. Paired Analysis based on Mixture Type and Property (Matched Lots and Sublots)

The next step was to conduct unpaired and paired analysis with the data. In the first case the lots were matched but eventually the sublot number between the QA and QC may have been different. The latter case required selecting projects that had the same number of sublot observations for the QA and QC data. The results are shown in tables 3.3 and 3.4. The paired analyses produced a significant improvement in the statistical agreement between the QA and QC data.

TABLE 3.3 Unpaired Analysis

	T_Test	F_Test
Rejected	630	501
Accepted	1840	1661
Total	2470	2162
Percent Accepted	74.5%	76.8%

Mix Type	Property	# of T_Test	QA_N	QC_N	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
G	ALL	139	2738	3816	51.8%	48.2%	131	67.9%	32.1%
H	ALL	423	2636	3762	80.6%	19.4%	380	82.6%	17.4%
R	ALL	1204	8165	10577	74.4%	25.6%	1028	75.7%	24.3%
S	ALL	67	352	441	82.1%	17.9%	60	86.7%	13.3%
V	ALL	637	4830	6011	74.7%	25.3%	563	76.0%	24.0%
ALL	AC	632	4750	6254	72.0%	28.0%	559	74.8%	25.2%
ALL	4.75	612	4664	6127	80.6%	19.4%	533	74.1%	25.9%
ALL	2.36	608	4660	6127	84.0%	16.0%	520	77.3%	22.7%
ALL	0.075	618	4647	6099	61.7%	38.3%	550	81.1%	18.9%

Mix Type	Property	# of T_Test	QA_N	QC_N	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
G	AC	35	686	960	62.9%	37.1%	33	57.6%	42.4%
G	4.75	34	684	954	47.1%	52.9%	33	69.7%	30.3%
G	2.36	35	685	953	62.9%	37.1%	32	78.1%	21.9%
G	0.075	35	683	949	34.3%	65.7%	33	66.7%	33.3%
H	AC	108	682	958	76.9%	23.1%	98	80.6%	19.4%
H	4.75	106	654	936	83.0%	17.0%	94	80.9%	19.1%
H	2.36	103	653	936	81.6%	18.4%	92	80.4%	19.6%
H	0.075	106	647	932	81.1%	18.9%	96	88.5%	11.5%
R	AC	309	2083	2707	71.2%	28.8%	269	73.2%	26.8%
R	4.75	299	2031	2629	83.3%	16.7%	253	72.3%	27.7%
R	2.36	295	2028	2631	86.4%	13.6%	243	76.1%	23.9%
R	0.075	301	2023	2610	57.1%	42.9%	263	81.0%	19.0%
S	AC	18	85	108	83.3%	16.7%	16	87.5%	12.5%
S	4.75	16	82	104	87.5%	12.5%	13	84.6%	15.4%
S	2.36	16	82	104	93.8%	6.3%	15	93.3%	6.7%
S	0.075	17	84	106	64.7%	35.3%	16	81.3%	18.8%
V	AC	162	1211	1518	71.0%	29.0%	143	76.2%	23.8%
V	4.75	157	1207	1498	80.3%	19.7%	140	72.9%	27.1%
V	2.36	159	1206	1497	84.9%	15.1%	138	75.4%	24.6%
V	0.075	159	1206	1498	62.9%	37.1%	142	79.6%	20.4%

** Table includes all the data.

TABLE 3.4 Paired Analysis

	T_Test	F_Test
Rejected	119	75
Accepted	506	527
Total	625	602
Percent Accepted	81.0%	87.5%

Mix Type	Property	# of T_Test	QA_N	QC_N	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
G	ALL	29	395	395	37.9%	62.1%	29	75.9%	24.1%
H	ALL	91	485	485	89.0%	11.0%	89	88.8%	11.2%
R	ALL	305	1453	1453	81.6%	18.4%	291	89.0%	11.0%
S	ALL	38	199	199	78.9%	21.1%	37	89.2%	10.8%
V	ALL	162	1080	1080	83.3%	16.7%	156	85.9%	14.1%
ALL	AC	155	854	854	81.3%	18.7%	155	89.0%	11.0%
ALL	4.75	155	903	903	83.9%	16.1%	145	86.9%	13.1%
ALL	2.36	157	924	924	86.6%	13.4%	146	87.7%	12.3%
ALL	0.075	158	931	931	72.2%	27.8%	156	86.5%	13.5%

Mix Type	Property	# of T_Test	QA_N	QC_N	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
G	AC	5	47	47	80.0%	20.0%	5	40.0%	60.0%
G	4.75	8	116	116	37.5%	62.5%	8	100.0%	0.0%
G	2.36	8	116	116	37.5%	62.5%	8	100.0%	0.0%
G	0.075	8	116	116	12.5%	87.5%	8	50.0%	50.0%
H	AC	23	132	132	87.0%	13.0%	23	91.3%	8.7%
H	4.75	23	118	118	91.3%	8.7%	22	81.8%	18.2%
H	2.36	23	119	119	87.0%	13.0%	22	90.9%	9.1%
H	0.075	22	116	116	90.9%	9.1%	22	90.9%	9.1%
R	AC	76	354	354	78.9%	21.1%	76	90.8%	9.2%
R	4.75	75	354	354	85.3%	14.7%	69	85.5%	14.5%
R	2.36	77	375	375	89.6%	10.4%	70	85.7%	14.3%
R	0.075	77	370	370	72.7%	27.3%	76	93.4%	6.6%
S	AC	10	49	49	80.0%	20.0%	10	90.0%	10.0%
S	4.75	9	50	50	77.8%	22.2%	8	87.5%	12.5%
S	2.36	9	50	50	88.9%	11.1%	9	100.0%	0.0%
S	0.075	10	50	50	70.0%	30.0%	10	80.0%	20.0%
V	AC	41	272	272	82.9%	17.1%	41	90.2%	9.8%
V	4.75	40	265	265	87.5%	12.5%	38	89.5%	10.5%
V	2.36	40	264	264	90.0%	10.0%	37	83.8%	16.2%
V	0.075	41	279	279	73.2%	26.8%	40	80.0%	20.0%

3.1.5 Analysis based on Mixtures Type, Mix Property, and Mix Band

For the High Polished mixtures, a relatively high rate of acceptance was observed, Tables 3.3 and 3.4. Thus it was decided to particularly focus on this group of data and further subcategorize the projects with respect to nominal maximum aggregate size (9.5, 12.5 and 19 mm). Tables 3.5 and 3.6 summarize the results for both unpaired and paired analyses. It can be seen that the acceptance rate increases with pairing, however the number of projects (# of performed tests) decreases significantly. As tabulated in Table 3.6, none of the 19 mm mixtures had projects with equal number of observations.

TABLE 3.5 Unpaired Analysis for High Polished Mixtures

Mix Type	Property	Mix Band	QA_N	QC_N	# of T_Test	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
H	AC	09	392	509	62	74.2%	25.8%	57	87.7%	12.3%
H	AC	12	227	347	38	78.9%	21.1%	35	77.1%	22.9%
H	AC	19	63	102	8	87.5%	12.5%	6	33.2%	66.8%
H	4.75	09	386	506	62	82.3%	17.7%	56	87.5%	12.5%
H	4.75	12	209	328	37	86.5%	13.5%	32	75.0%	25.0%
H	4.75	19	59	102	7	71.4%	28.6%	6	50.0%	50.0%
H	2.36	09	385	506	59	84.1%	15.9%	55	83.6%	16.4%
H	2.36	12	209	328	37	83.8%	16.2%	31	77.4%	22.6%
H	2.36	19	59	102	7	74.4%	25.6%	6	66.7%	33.3%
H	0.075	09	382	505	61	85.2%	14.8%	56	91.1%	8.9%
H	0.075	12	207	326	37	70.3%	29.7%	34	94.1%	5.9%
H	0.075	19	58	101	8	100.0%	0.0%	6	33.3%	66.7%

TABLE 3.6 Paired Analysis for High Polished Mixtures

Mix Type	Property	Mix Band	QA_N	QC_N	# of T_Test	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
H	AC	09	67	67	14	86.0%	14.0%	14	93.0%	7.0%
H	AC	12	64	64	9	89.0%	11.0%	9	89.0%	11.0%
H	AC	19	No Data							
H	4.75	09	66	66	14	100.0%	0.0%	14	100.0%	0.0%
H	4.75	12	51	51	9	78.0%	22.0%	8	50.0%	50.0%
H	4.75	19	No Data							
H	2.36	09	67	67	14	93.0%	7.0%	13	100.0%	0.0%
H	2.36	12	51	51	9	78.0%	22.0%	9	78.0%	22.0%
H	2.36	19	No Data							
H	0.075	09	64	64	13	92.0%	8.0%	13	85.0%	15.0%
H	0.075	12	51	51	9	89.0%	11.0%	9	100.0%	0.0%
H	0.075	19	No Data							

3.1.6 Analysis based on Deviations from the Target Values

In the next step of the analysis, the deviations from the target values were considered for all mixtures together. One of the benefits of such approach is that the distribution of the deviations is immediately evident for both QA and QC data. Also the variability of such data sets in relation to the tolerances identified for every mix property can be immediately assessed. Such analyses also allow for the different target values from one project to the next, especially for asphalt content. As shown in Figures 3.1 to 3.4 (representing the AC content, and percent passing 4.75mm, 2.36mm, and the 0.075mm) the dispersion of the QA data is larger than that for

the QC data. The QC data are clearly more concentrated towards the central tendency (in this case higher frequency around the zero deviation from the target values).

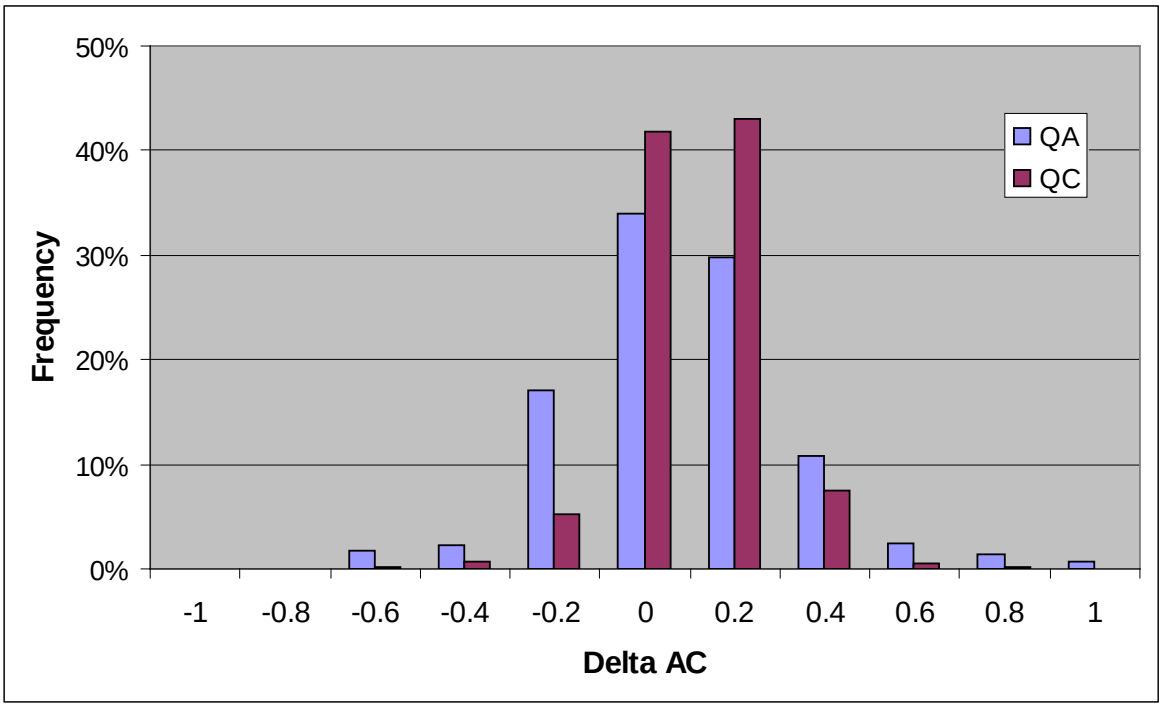

FIGURE 3.1 Deviations from the Target Values for AC

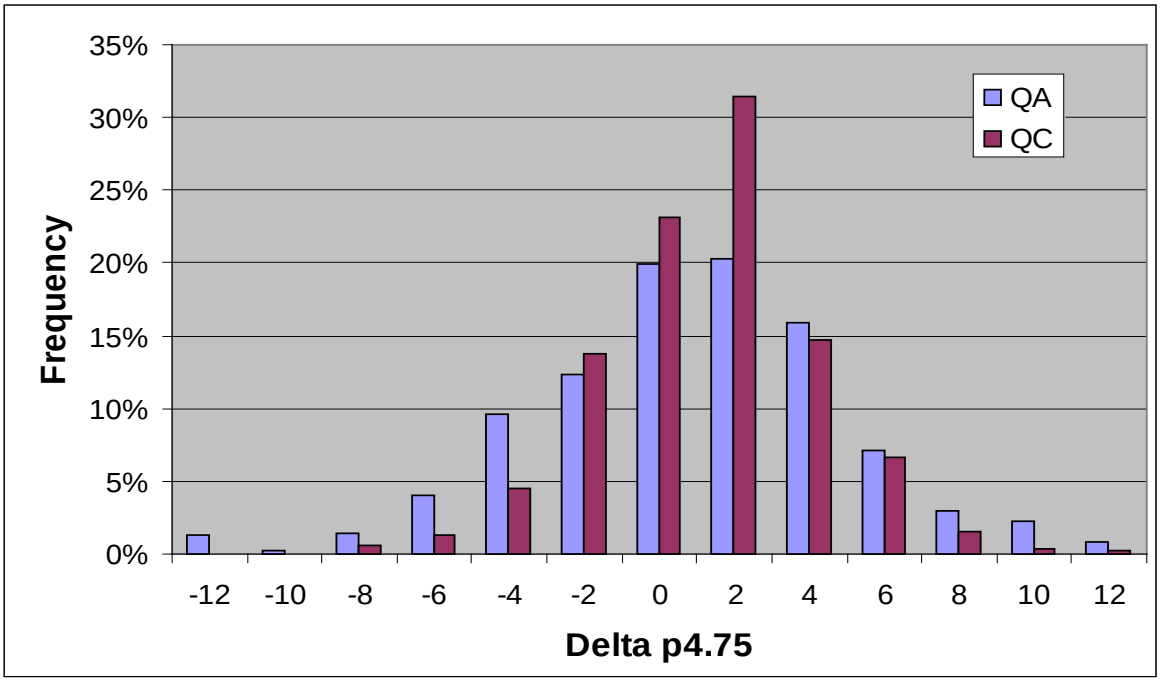

FIGURE 3.2 Deviations from the Target Values for 4.75mm

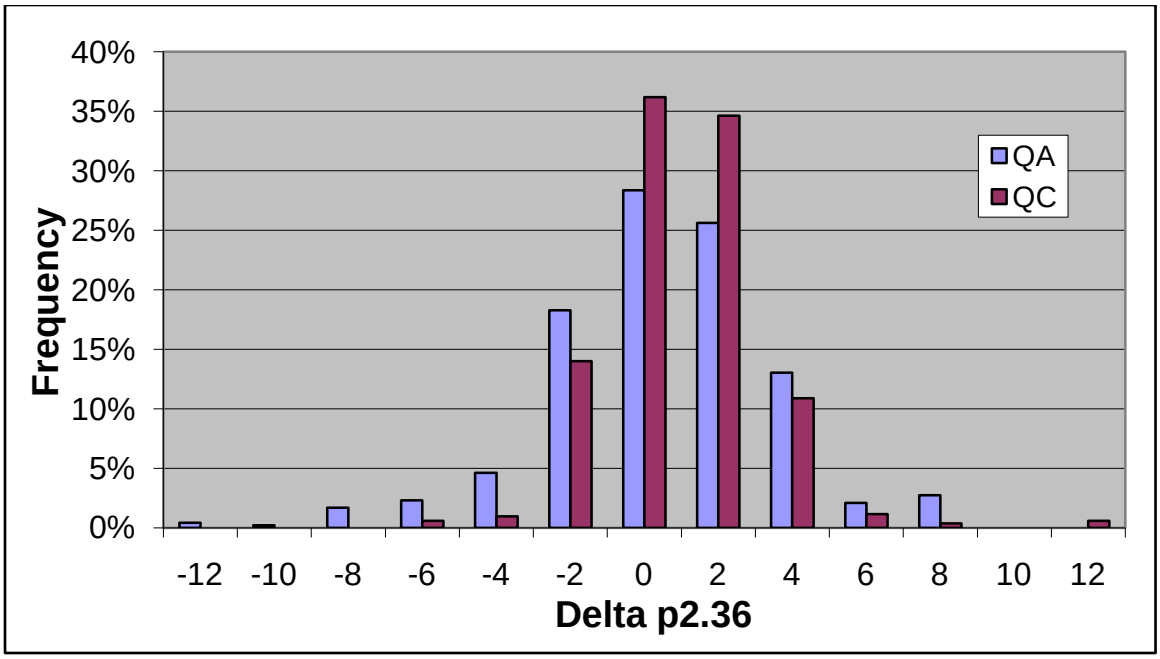

FIGURE 3.3 Deviations from the Target Values for 2.36mm

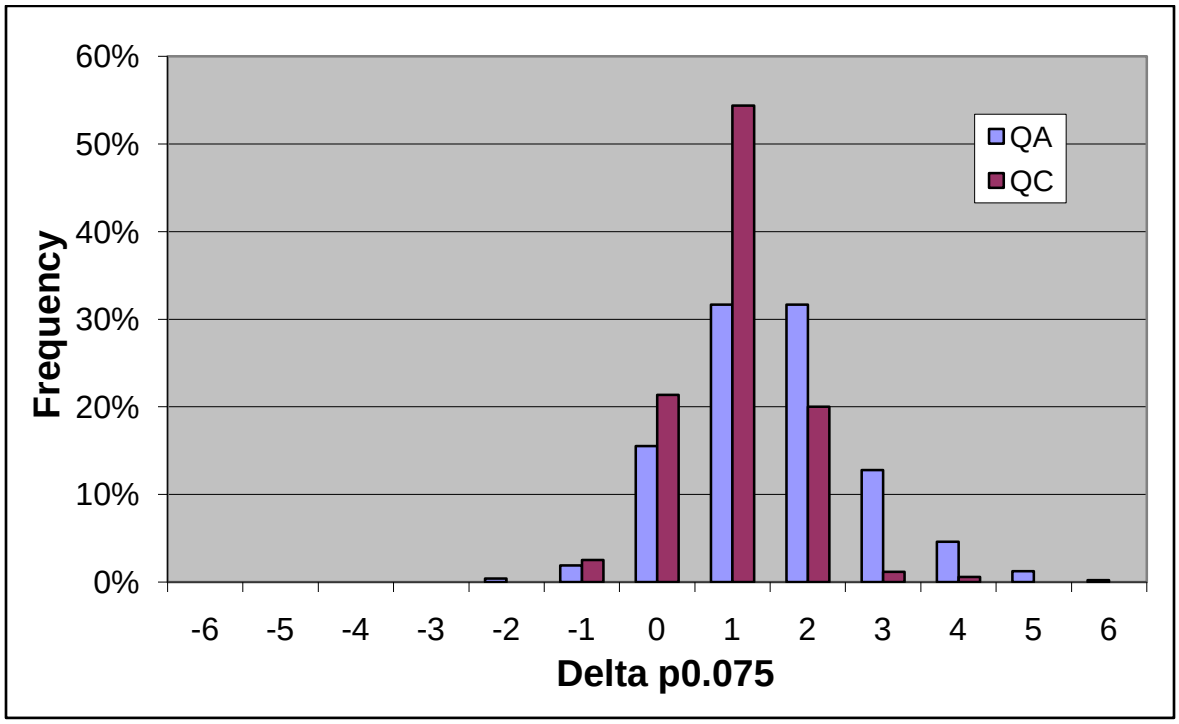

FIGURE 3.4 Deviations from the Target Values for 0.075mm

Further review of the QA and QC databases revealed that for certain projects and mixtures there was more than one target for the same project. These projects, totaling about 138

JMFIDs, were therefore censored from the database. After this filtering, the F and *t* tests were repeated and the results in tables 3.7- 3.11 were obtained. Even after all of this scrutiny and scrubbing of the database, , the acceptance rate for some of the mixtures were relatively low.

TABLE 3.7 F and *t* Analysis on Delta for Projects with Unique Target Values – Mix High Polished

Mix Type	Property	Mix Band	QA_N	QC_N	# of T_Test	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
H	AC	09	387	504	26	62.0%	38.0%	25	92.0%	8.0%
H	AC	12	225	345	16	87.5%	12.5%	14	85.7%	14.3%
H	AC	19	62	101	3	100.0%	0.0%	1	0.0%	100.0%
H	4.75	09	382	502	27	81.0%	19.0%	25	84.0%	16.0%
H	4.75	12	207	326	16	81.3%	18.7%	15	80.0%	20.0%
H	4.75	19	57	99	2	100.0%	0.0%	1	0.0%	100.0%
H	2.36	09	378	496	25	88.0%	12.0%	25	80.0%	20.0%
H	2.36	12	207	326	16	87.5%	12.5%	12	75.0%	25.0%
H	2.36	19	57	99	2	100.0%	0.0%	1	0.0%	100.0%
H	0.075	09	377	500	26	84.6%	15.4%	25	92.0%	8.0%
H	0.075	12	205	324	16	87.5%	12.5%	15	100.0%	0.0%
H	0.075	19	57	100	3	100.0%	0.0%	1	0.0%	100.0%

TABLE 3.8 F and *t* Analysis on Delta for Projects with Unique Target Values – Mix Gap Grade

Mix Type	Property	Mix Band	QA_N	QC_N	# of T_Test	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
G	AC	09	99	133	6	50.0%	50.0%	6	83.3%	16.7%
G	AC	12	587	827	29	65.5%	34.5%	27	51.9%	48.1%
G	AC	19					NO DATA			
G	4.75	09	98	133	6	50.0%	50.0%	6	66.7%	33.3%
G	4.75	12	585	819	28	46.4%	53.6%	27	70.4%	29.6%
G	4.75	19					NO DATA			
G	2.36	09	98	133	6	66.7%	33.3%	5	100.0%	0.0%
G	2.36	12	587	820	29	62.1%	37.9%	27	74.1%	25.9%
G	2.36	19					NO DATA			
G	0.075	09	98	133	6	33.3%	66.7%	6	66.7%	33.3%
G	0.075	12	585	816	29	34.5%	65.5%	27	66.7%	33.3%
G	0.075	19					NO DATA			

TABLE 3.9 F and *t* Analysis on Delta for Projects with Unique Target Values – Mix S

Mix Type	Property	Mix Band	QA_N	QC_N	# of T_Test	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
S	AC	09	8	12	3	66.7%	33.3%	2	100.0%	0.0%
S	AC	12	64	79	11	65.5%	34.5%	10	51.9%	48.1%
S	AC	19	13	17	4	100.0%	0.0%	4	100%	0.0%
S	4.75	09	7	10	2	100.0%	0.0%	1	100.0%	0.0%
S	4.75	12	64	79	11	81.8%	18.2%	9	77.8%	22.2%
S	4.75	19	11	15	4	75.0%	25.0%	4	75.0%	25.0%
S	2.36	09	7	10	2	100.0%	0.0%	2	100.0%	0.0%
S	2.36	12	64	79	11	90.9%	9.1%	10	90.0%	10.0%
S	2.36	19	11	15	3	100.0%	0.0%	3	100.0%	0.0%
S	0.075	09	7	10	2	50.0%	50.0%	2	100.0%	0.0%
S	0.075	12	64	79	11	63.6%	36.4%	10	80.0%	20.0%
S	0.075	19	13	17	4	75.0%	25.0%	4	75.0%	25.0%

TABLE 3.10 F and *t* Analysis on Delta for Projects with Unique Target Values – Mix Rap

Mix Type	Property	Mix Band	QA_N	QC_N	# of T_Test	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
R	AC	09	409	532	69	63.8%	36.2%	61	83.6%	16.4%
R	AC	12	667	933	99	70.7%	29.3%	90	70.0%	30.0%
R	AC	19	538	703	99	79.8%	20.2%	80	58.0%	42.0%
R	AC	25	283	310	36	69.4%	30.6%	32	75.0%	25.0%
R	AC	37	149	192	6	33.3%	66.7%	6	16.7%	83.3%
R	4.75	09	401	522	67	77.6%	22.4%	58	65.5%	34.5%
R	4.75	12	661	920	98	83.7%	16.3%	86	75.6%	24.4%
R	4.75	19	514	662	93	90.3%	9.7%	74	75.7%	24.3%
R	4.75	25	268	294	35	80.0%	20.0%	29	72.4%	27.6%
R	4.75	37	144	189	6	50.0%	50.0%	6	50.0%	50.0%
R	2.36	09	396	517	65	84.6%	15.4%	55	74.5%	25.5%
R	2.36	12	659	916	97	90.7%	9.3%	82	79.3%	20.7%
R	2.36	19	515	664	93	88.2%	11.8%	71	78.9%	21.1%
R	2.36	25	266	291	34	76.5%	23.5%	29	72.4%	27.6%
R	2.36	37	144	189	6	66.7%	33.3%	6	33.3%	66.7%
R	0.075	09	401	522	67	65.7%	34.3%	61	66.7%	33.3%
R	0.075	12	658	903	99	53.5%	46.5%	89	84.3%	15.7%
R	0.075	19	516	666	94	60.6%	39.4%	77	79.2%	20.8%
R	0.075	25	268	293	35	42.9%	57.1%	30	83.3%	16.7%
R	0.075	37	143	189	6	50.0%	50.0%	6	33.3%	66.7%

TABLE 3.11 F and *t* Analysis on Delta for Projects with Unique Target Values – Mix Virgin

Mix Type	Property	Mix Band	QA_N	QC_N	# of T_Test	% T_Test Accepted	%T_Test Rejected	# of F_Test	%F_Test Accepted	%F Rejected
V	AC	04	43	58	12	66.7%	33.3%	10	100.0%	0.0%
V	AC	09	254	329	37	83.8%	16.2%	34	73.5%	26.5%
V	AC	12	720	816	74	63.5%	36.5%	71	73.2%	26.8%
V	AC	19	138	228	34	73.5%	26.5%	24	79.2%	20.8%
V	AC	25	31	62	5	80.0%	20.0%	4	75.0%	25.0%
V	4.75	04	42	56	11	81.8%	18.2%	9	88.9%	11.1%
V	4.75	09	254	321	37	83.8%	16.2%	34	79.4%	20.6%
V	4.75	12	714	807	72	75.0%	25.0%	69	69.6%	30.4%
V	4.75	19	136	223	32	87.5%	12.5%	24	66.7%	33.3%
V	4.75	25	31	59	5	80.0%	20.0%	4	75.0%	25.0%
V	2.36	04	43	58	12	83.3%	16.7%	9	100.0%	0.0%
V	2.36	09	254	321	37	81.1%	18.9%	34	76.5%	23.5%
V	2.36	12	715	810	73	83.6%	16.4%	68	70.6%	29.4%
V	2.36	19	137	222	32	93.8%	6.3%	24	120.8%	-20.8%
V	2.36	25	31	59	5	80.0%	20.0%	3	66.7%	33.3%
V	0.075	04	42	56	11	63.6%	36.4%	10	90.0%	10.0%
V	0.075	09	254	321	37	51.4%	48.6%	34	82.4%	17.6%
V	0.075	12	715	810	73	63.0%	37.0%	70	78.6%	21.4%
V	0.075	19	137	224	33	75.8%	24.2%	24	79.2%	20.8%
V	0.075	25	31	59	5	60.0%	40.0%	4	50.0%	50.0%

In all analyses, regardless of whether the entire QA and QC datasets or just subsets representing specific mixture types were considered, a significant number of F and *t* tests were rejected. The inescapable conclusion is that the QA and QC data cannot be considered as representative of the same population, and thus the null hypothesis (Ho) must be rejected. Furthermore, the analyses indicated that

i) differences in variability are greater than differences in mean and

ii) The QA data show higher variability than the QC data.

Some of these differences are certainly due to different sampling locations. Although Paired-t results compare more often than unpaired, there are still several significant differences between paired results (15-20% overall). Some of these differences may have to do with the difficulty in matching the lots and sublots between QA and QC data, primarily due to:

i) Discrepancies in the database, and

ii) Lack of using a common and unique identification for the material departing the plant and the one behind the paver.

In other words a better tracking technique is needed in this area.

3.2 Transfer Functions Between QA and QC Data

The results of the F and *t* analysis on the QA and QC data indicated that these two data sets represent statistically different populations. Based on the interaction and feedback of the MSHA research project engineer, it was decided to examine whether it was possible to define transfer functions between the material properties of the QA and QC data.

In order to examine whether such relationships were possible, the research team directed the effort of the analysis towards the premium SHA asphalt mixture where better quality control is expected. Thus, the analyses were oriented towards the gap graded 12.5mm mixture. The QA and QC data from the gap-graded projects were matched on a lot-by-lot basis and the average value of each lot was calculated and plotted in Figures 3.5 through 3.8. As it can be seen from these figures there is a significance scatter between these two data sets providing very poor correlations between the QA and QC data for any mixture property.

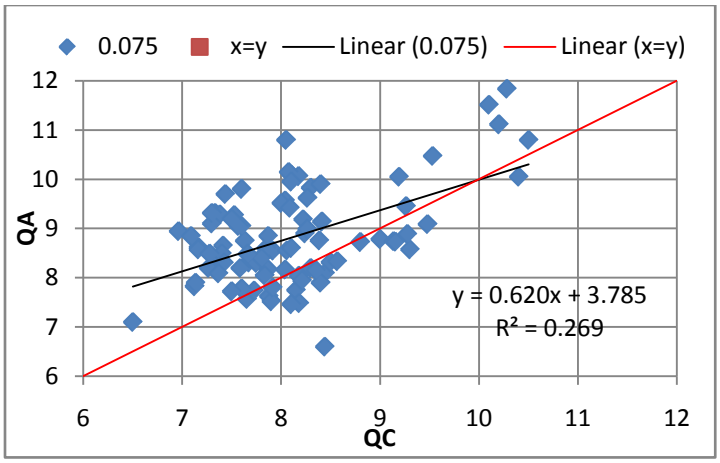

FIGURE 3.5 Comparison of QA & QC Data for the 0.075mm of the 12.5 Gap Graded Mixtures

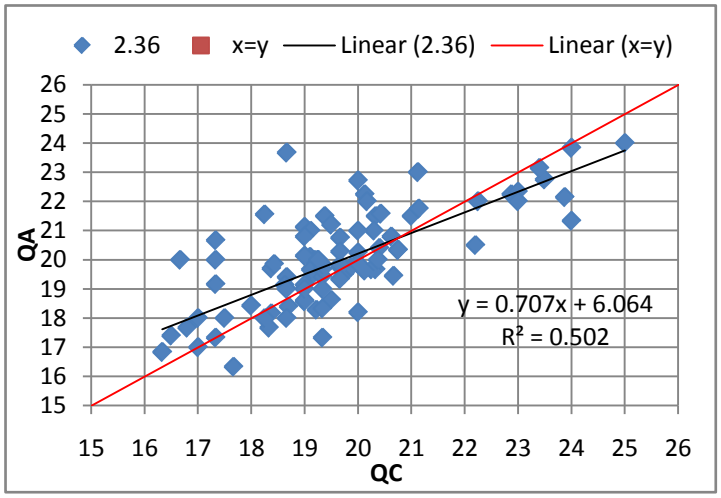

FIGURE 3.6 Comparison of QA & QC Data for the 2.36 mm of the 12.5 Gap Graded Mixtures

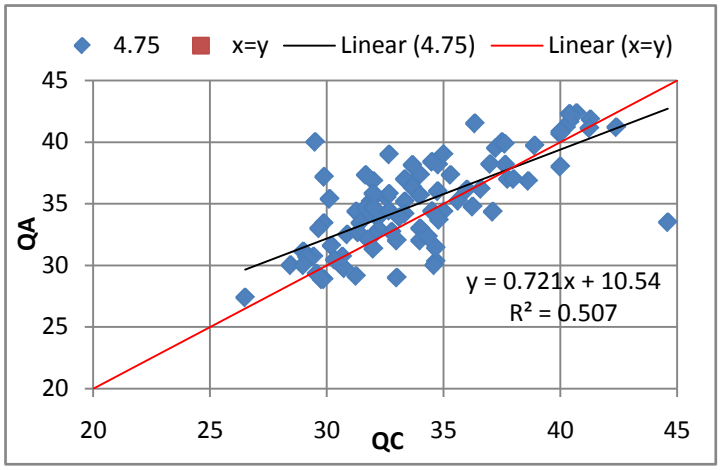

FIGURE 3.7 Comparison of QA & QC Data for the 4.75mm of 12.5 Gap Graded Mixtures

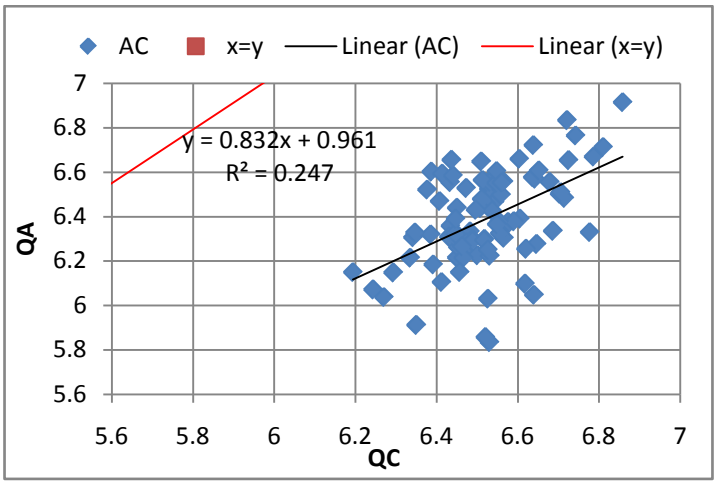

FIGURE 3.8 Comparison of QA & QC Data for the AC Content of 12.5 Gap Graded Mixtures

CHAPTER 4 TYPE I AND TYPE II ERROR ANALYSIS & OPERATION CHARACTERISTIC (OC) CURVES

4.1. Definitions

The "FHWA Optimal Procedures for Quality Assurance Specifications" report (Burati et. al. 2003) provides the following definitions for the OC curves, type I and type II errors:

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. [The probability of having RQL material or construction accepted (at any pay) may be considerably greater than the buyer's risk.

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 EP of 100 percent.]

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.

Based on these terms the seller's risk (α) and the buyer's risk (β) are calculated at AQL and RQL respectively.

As mentioned previously there are generally two types of acceptance plans: 1) the accept/reject acceptance plans and 2) acceptance plans that include pay adjustment provisions. The development of traditional OC curves and the definitions of α and β risks are more appropriate for the first case and less relevant to the current SHA specification that include pay adjustment provisions. Nevertheless, the examination of these parameters was included in this study as an exercise of probability analysis involved if a pay provision is not considered, and thus, it was limited to only the premium (gap graded) SHA mixtures. The analysis and results are reported in this chapter.

4.2. Construction of OC Curves and Calculation of Type I and Type II Errors

4.2.1 Assessing the Current Conditions

In order to conduct the OC analysis and identify the alpha and beta risks for each of the mixture characteristics (i.e., 0.075, 2.36, 4.75, and AC content), the population distribution for each was evaluated using the QA data. Based on the population distribution values, representative projects and lots were selected to run the OC curve analysis and estimate the Type I and II errors. The results for the gap graded mixtures, representing the premium MSHA mixture, are presented herein.

F and t test were performed to identify lots that better match the characteristics of the population for each of the mixture properties. Table 4.1 presents the representative lots for the 0.075, 2.36, 4.75, and AC mixture proprieties of the gap graded mixtures. The table includes information on the ProjectID, JMFID, lot number, and number of sublots, n, within a lot.

TABLE 4. 1 Representative Lots for the 0.075, 2.36, 4.75, and AC Content of Gap Graded Mixtures

Property	ProjectID	JMFID	Lot#	n
0.075	GA6445177	W13512G4D01F	2	9
2.36	FT458M80	N13812G4F01F	3	7
4.75	BA481B51	N08312G4F02F	1	8
AC	AA416B51	N05109G4F01F	1	9

Note: n= number of sublots

Based on these typical lots, the following OC curves were developed, Figures 4.1 to 4.4 The OC curves were plotted for all the “typical” lots representing the population characteristics (distribution) and with varying sample size, n. In order to better understand the role of sample size (n), this value was varied and the curves were re-plotted.

The OC curves were developed using the procedure followed by Villiers et al. (2003) and using the standard error of the population in order to relate PWL and probability of acceptance.

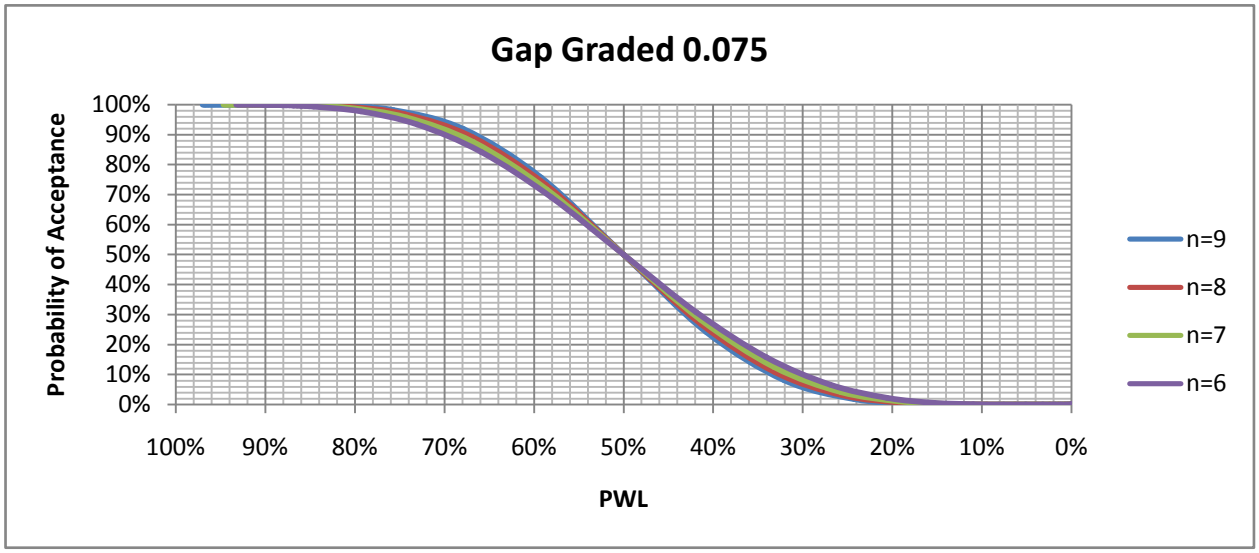

FIGURE 4.1 OC Curve for 0.075 mm of Gap Graded Mixtures

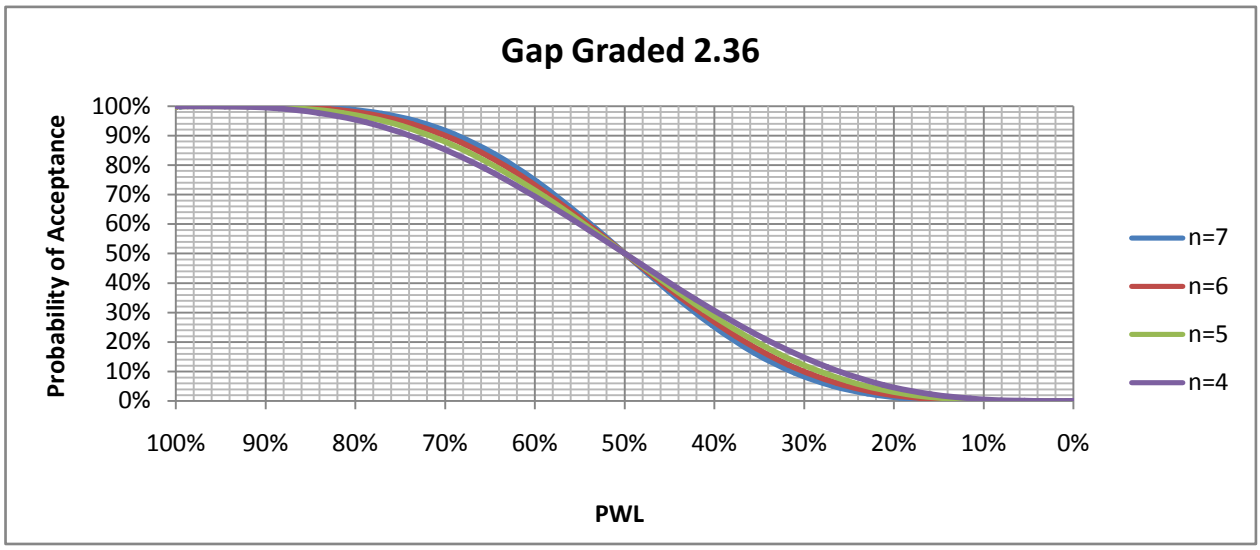

FIGURE 4.2 OC Curve for 2.36 mm of Gap Graded Mixtures

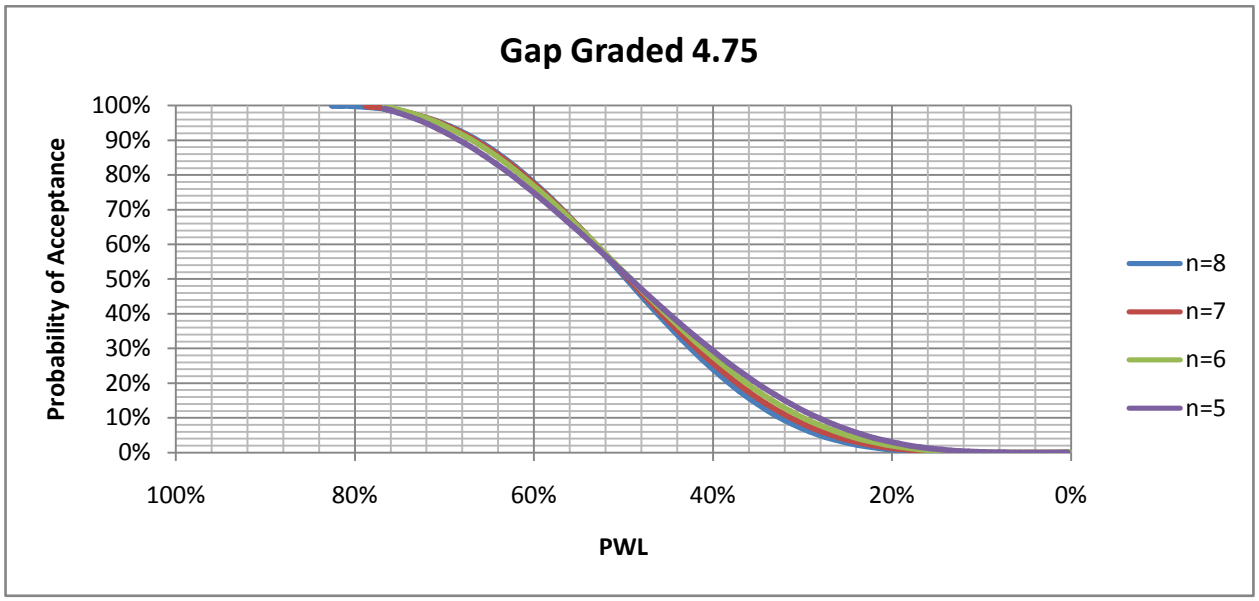

FIGURE 4.3 OC Curve for 4.75 mm of Gap Graded Mixtures

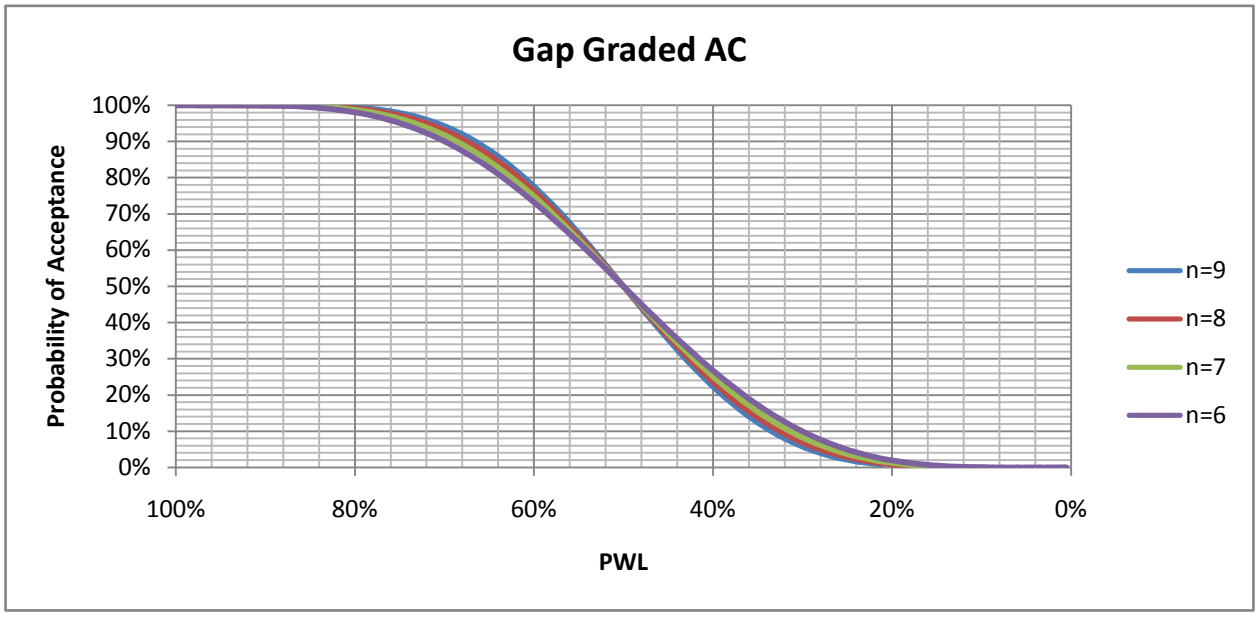

FIGURE 4.4 OC Curve for AC content of Gap Graded Mixtures

As illustrated in figures 4.1through 4.4, for a sample size n=6 , the α and β risks corresponding to an AQL of 90% and RQL of 40 % (back calculated from equation 3) are equal to about 0% and 26.5% respectively, Table 4.2. The effects of changing the sample size n can be also assessed from the OC Figures.

TABLE 4.2 Risks Based on AQL= 90% and RQL = 40% for n=6.

Property	Tolerance	α @ AQL=90%	β @ RQL=40%
0.075	± 2	0.0%	26.5%
2.36	± 5	0.1%	26.8%
4.75	± 5	0.0%	27.6%
AC	± 0.5	0.1%	26.3%

4.2.2 Modifying AQL and RQL to balance the risks (α= 1% and β= 5%)

Since the α and β risks are far from the typical values of 1% and 5% respectively used in practice (ASSHTO R-9), new values of AQL and RQL may be identifying for balancing these risks. Table 4.3 provides the values of AQL and RQL that result in α and β risks of 1% and 5% respectively.

TABLE 4.3 AQL and RQL for *α= 1% and β= 5% (*n=6).

Property	Tolerance	AQL @ α=1%	RQL @ β=5%
0.075	± 2	82.9%	25.0%
2.36	± 5	82.9%	25.1%
4.75	± 5	75.6%	25.0%
AC	± 0.5	83.4%	25.9%

4.2.3 Revised Specification Tolerances for α= 1% and β= 5%

Based on the revised values of AQL and RQL providing α= 1% and β= 5% risks, Table 4.3, new tolerance may be defined for the specification. Based on the recommendations of the FHWA Optimal Procedures for QA Specifications study (Burati et. al. 2003), these new tolerances can be determined by first calculating the standard normal Z-values corresponding to each AQL value and then multiplying it by the standard deviation of the representative lot. The new set of specification tolerances (shown in Table 4.4) were obtained by following this

procedure. The important question is whether such tolerances represent realistic achievable levels of production by the paving industry.

TABLE 4.4 Revised Specification tolerances for α= 1% and β= 5%.

Property	Tolerance
0.075	0.9
2.36	1.2
4.75	2.9
AC	0.15

The α and β risk analysis and OC calculations provided an initial assessment of the risks involved with the current specifications. However, these analyses were not expanded to the remaining MSHA mixtures since such risks are assessed for each individual mixture property rather than providing an assessment of a combined risk associated with all mixture properties, as it is the case of the combined MSHA specification. Also, as indicated previously the above approach is primarily used for accept/ reject plans. Since the SHA specs include pavement adjustment provisions, the focus of the research was directed toward the expected pay (EP) calculations approach using simulation analysis.

CHAPTER 5 SIMULATION ANALYSIS

The purpose of the simulation analysis was to examine the impact of the current Hot Mix Asphalt (HMA) production quality on the composite PWL and pay factor, and assess the impact of alternative scenarios in terms of specification tolerances or pay equations. In these analyses the revised 2008 HMA specs were used. Only dense graded HMA mixtures were considered in the simulation because of the comparatively large amount of data available for these mixtures in the SHA database. The simulation tool developed under this study considers the four HMA mixture parameters (AC content and percent passing the 0.075, 2.36, 4.75 mm sieves) and their correlations for calculating the composite pay factor CMPWSL and the expected mix pay factor (MF). An example of the correlations between the four mix properties for dense graded mixtures is shown in Table 5.1. Preliminary analyses have shown that the correlation effects of the four HMA mix properties have little impact on the pay factor analysis. Example calculations are shown in appendix section A.4. Details on the Monte Carlo simulation algorithms and associate program code can be found in the appendix. Once the simulation code was verified to make sure that the algorithms were working properly and providing reasonable and rational responses, several alternative scenarios were investigated. Mean values and standard deviations for the specification variables were based on all dense graded QA data, excluding JMFIDs with multiple target values. The statistical results for this data population are tabulated in the Table 5.2.

TABLE 5.1 Correlations Between Mix Parameters for Dense Graded Mixtures

Property	0.075	2.36	4.75	AC
0.075	1	0.338	0.208	0.242
2.36	0.338	1	0.562	0.261
4.75	0.208	0.562	1	0.305
AC	0.242	0.261	0.305	1

TABLE 5.2 Population Characteristics

Property	Delta Mean*	Std. Dev.
0.075	0.992	1.20
2.36	-0.192	3.88
4.75	0.066	5.60
AC	-0.002	0.31

*Deviations from the target values

5.1 Analysis Based on Previous Specifications

The first set of analyses were based on the following pay equation and the population characteristics shown in Table 5.2.

$$\begin{cases} MF = 0.55 + 0.5CMPWSL \\ if\ CMPWSL\ \geq 90\%\ MF = 1 \\ if\ CMPWSL < 40\%\ MF = 0 \end{cases} \qquad \textbf{EQUATION 5.1}$$

5.1.1 Reducing Asphalt Content Variability

The goal of this analysis was to examine how much a producer might be able to reduce the asphalt content and still have an acceptable product, assuming that he/she can improve production control and thus reduce production variability (standard deviation). All the gradations (0.075, 2.36 and 4.75) were kept at the population characteristics values. The standard deviation of AC content was progressively reduced to 75%, 50% and 25% of the population value. The results were plotted in Figure 5.1, for a constant MF of 97.5% representing the value obtained based on the current population characteristics at the long run. As shown in Figure 5.1, a contractor that is able to produce a HMA mixture with 75% lower variability (0.25 SD/SD_{pop}) than the current QA population variability can reduce the AC content by 0.4% from the target and receive the same MF. Considering that the current tolerance for AC content is ±0.5%, this change in AC content is significant.

Next the effect of reducing production variability of AC content on CMPWSL and MF was examined, all remaining parameters (including population means for all mixture parameters

and variances for the three gradation percent passing) were at the population values. As shown in Figures 5.2 and 5.3, if a contractor reduces production variability by 75% (0.25 SD/SD_{pop})while aiming for the target AC content, it can increase its CMPWSL from 86% to about 93% and receive an MF of about 99.7% instead of 97.5% (corresponding at SD/SD_{pop}=1).

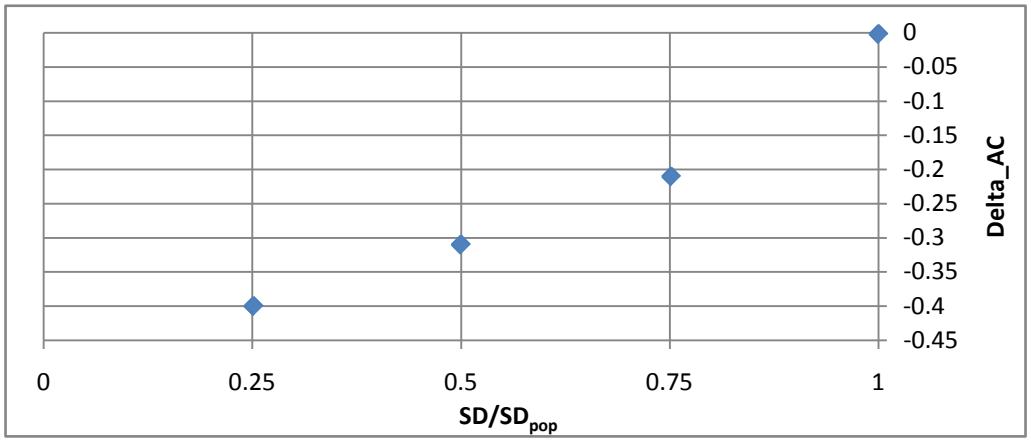

FIGURE 5.1 Effect of Reduction in Asphalt Content Variability

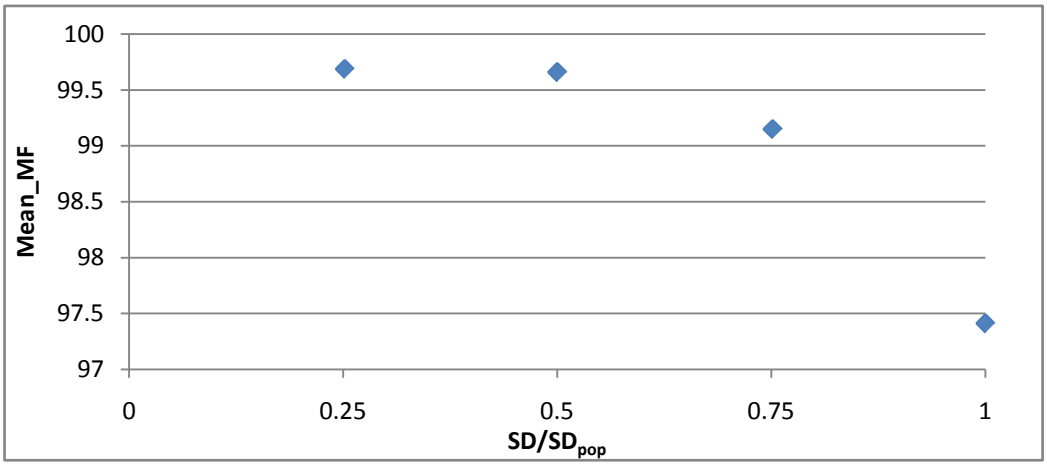

FIGURE 5.2 Effect of Reduction in Asphalt Content Variability on MF

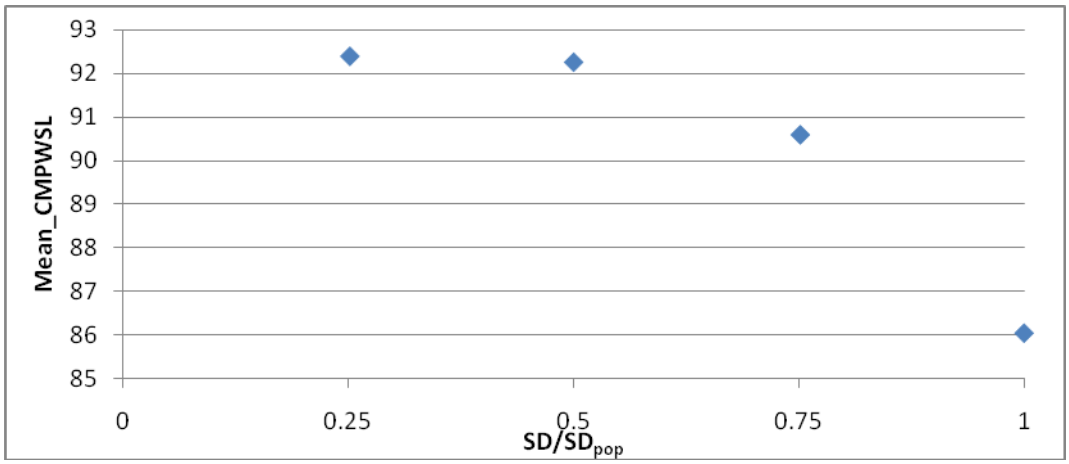

FIGURE 5.3 Effect of reduction in asphalt content variability on CMPWSL

5.1.2 Modifying Specification Tolerances

The next set of analysis examined the effects of specification limit (tolerance) changes on the average MF and CMPWSL. Based on the current specifications, the tolerance for AC is ±0.5%. All other tolerances were kept constant and only the AC tolerance was varied. The results are shown in Table 5.3 and Figures 5.4 and 5.5. A change in the tolerance of AC content of about 20% will result in a change of 4% CMPWSL and 1.4% in MF.

TABLE 5.3 Effects of Change in AC Specification Tolerance

AC_Tol	%Change	Mean_CM	Mean_MF	% Change CM	% Change MF
1	100%	92.4	99.7	7%	2.4%
0.75	50%	91.6	99.5	6%	2.1%
0.6	20%	89.4	98.7	4%	1.4%
0.55	10%	88.0	98.2	2%	0.8%
0.5	0%	86.0	97.4	0%	0.0%
0.45	-10%	83.6	96.3	-3%	-1.1%
0.4	-20%	80.7	95.0	-6%	-2.4%
0.25	-50%	66.9	88.4	-22%	-9.3%

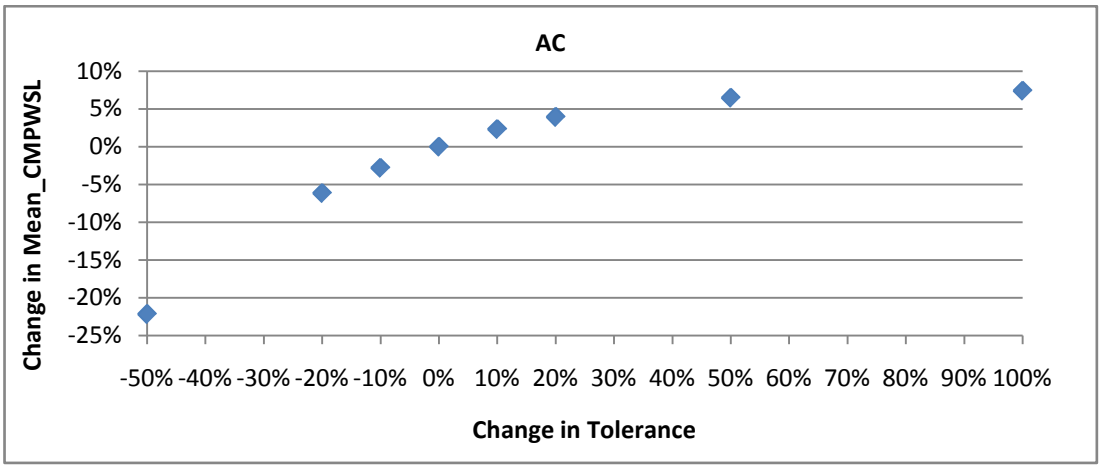

FIGURE 5.4 Effects of Change in AC Specification Tolerance on CMPWSL

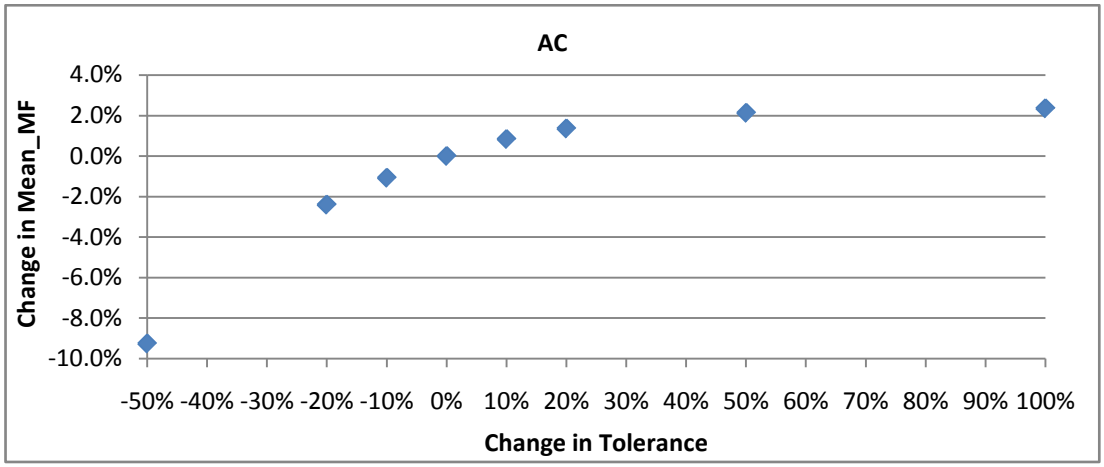

FIGURE 5.5 Effects of Change in AC Specification Tolerance on MF

Similarly, the effects of changing the 0.075mm percent passing specification tolerance was also examined. The current specification has a tolerance of ±2%. The results of varying the 0.075 mm percent passing tolerance while holding all other constant are shown in Table 5.4 and Figures 5.6 and 5.7.

TABLE 5.4 Effects of Change in 0.075 Specification Tolerance on MF

0.075_Tol	%Change	Mean_CM	Mean_MF	% Change CM	% Change MF
4	100%	90.9	98.8	5.6%	1.5%
3	50%	89.8	98.5	4.4%	1.2%
2.4	20%	88.0	98.1	2.3%	0.7%
2.2	10%	87.3	97.8	1.5%	0.5%
2	0%	86.0	97.4	0.0%	0.0%
1.8	-10%	84.8	96.9	-1.5%	-0.5%
1.6	-20%	83.4	96.4	-3.1%	-1.0%
1	-50%	78.0	94.0	-9.3%	-3.5%

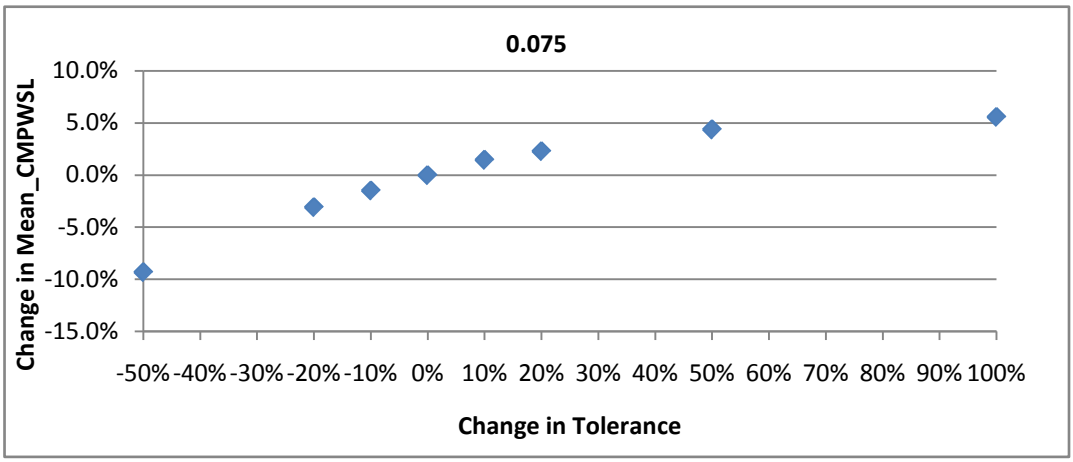

FIGURE 5.6 Effects of Change in 0.075 Specification Tolerance on CMPWSL

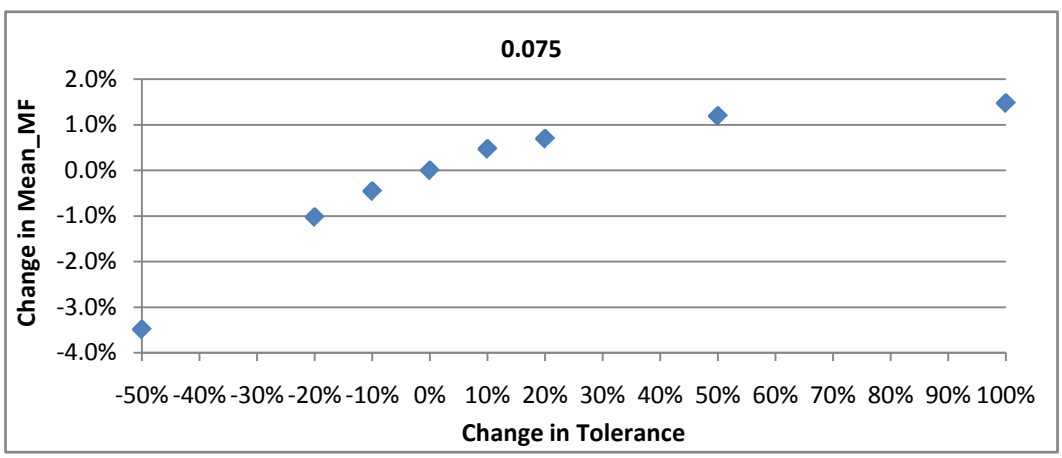

FIGURE 5.7 Effects of Change in 0.075 Specification Tolerance on MF

The effects of changing the 2.36 percent passing specification tolerance was then examined. The current specifications have a tolerance of ±5%. The results of varying the

2.36mm percent passing tolerance while holding all other tolerances constant are shown in Table 5.5 and Figures 5.8 and 5.9.

TABLE 5.5 Effects of Change in 2.36 Specification Tolerance on MF

2.36_Tol	%Change	Mean_CM	Mean_MF	% Change CM	% Change MF
10	100%	87.5	97.9	1.76%	0.40%
7.5	50%	87.0	97.7	1.13%	0.20%
6	20%	86.6	97.6	0.71%	0.07%
5.5	10%	86.4	97.5	0.49%	0.02%
5	0%	86.0	97.4	0.00%	-0.12%
4.5	-10%	85.7	97.3	-0.28%	-0.21%
4	-20%	85.4	97.2	-0.65%	-0.32%
2.5	-50%	83.9	96.6	-2.45%	-0.90%

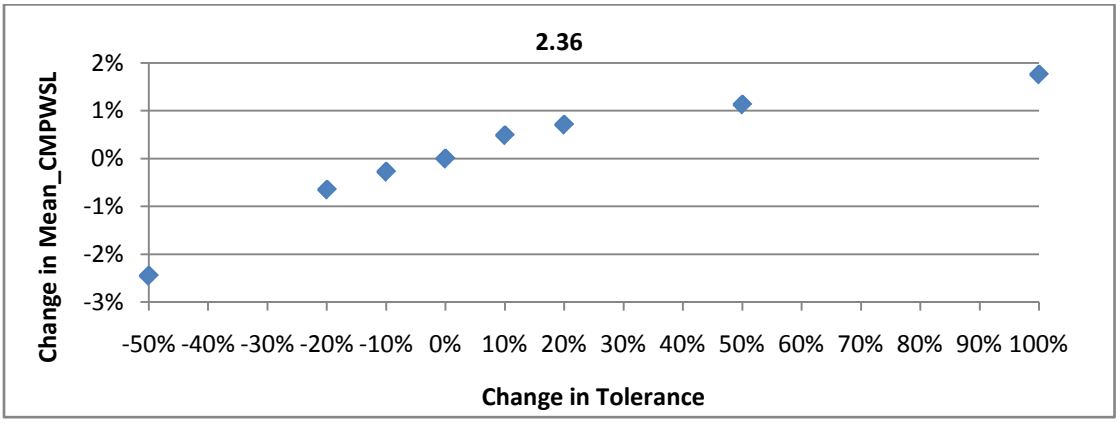

FIGURE 5.8 Effects of Change in 2.36 Specification Tolerance on CMPWSL

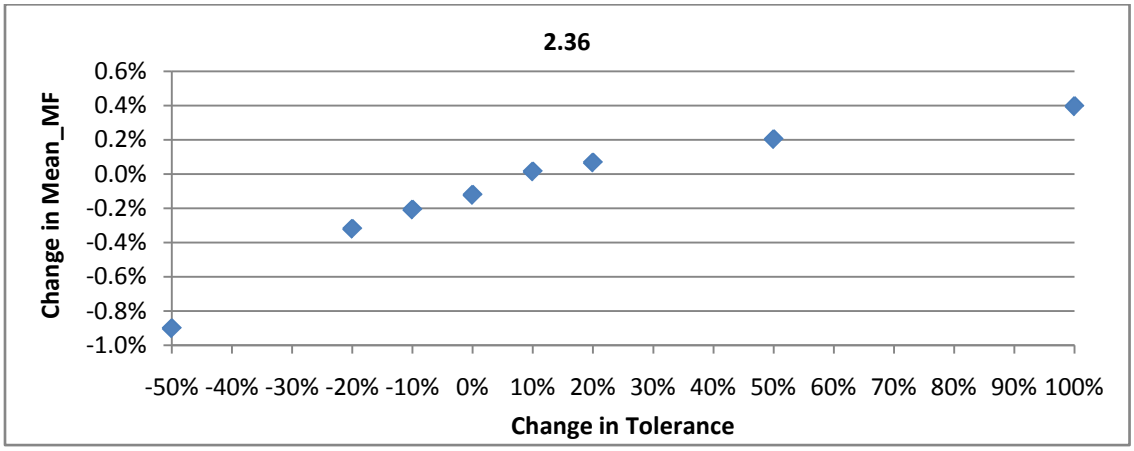

FIGURE 5.9 Effects of Change in 2.36 Specification Tolerance on MF

Finally, the effects of changing the 4.75 percent passing specification tolerance was examined. The current specifications has a tolerance of ±7%. The results from varying the 4.75mm percent passing tolerance while holding all others tolerances constant are shown in Table 5.6 and Figures 5.10 and 5.11.

TABLE 5.6 Effects of Change in 4.75 Specification Tolerance on MF

4.75_Tol	%Change	Mean_CM	Mean_MF	% Change CM	% Change MF
14	100%	87.5	97.9	1.7%	0%
10.5	50%	87.1	97.8	1.3%	0.3%
8.4	20%	86.6	97.6	0.8%	0.1%
7.7	10%	86.4	97.5	0.4%	0.0%
7	0%	86.0	97.4	0.0%	-0.1%
6.3	-10%	85.8	97.3	-0.3%	-0.2%
5.6	-20%	85.4	97.2	-0.6%	-0.3%
3.5	-50%	83.9	96.6	-2.5%	-1%

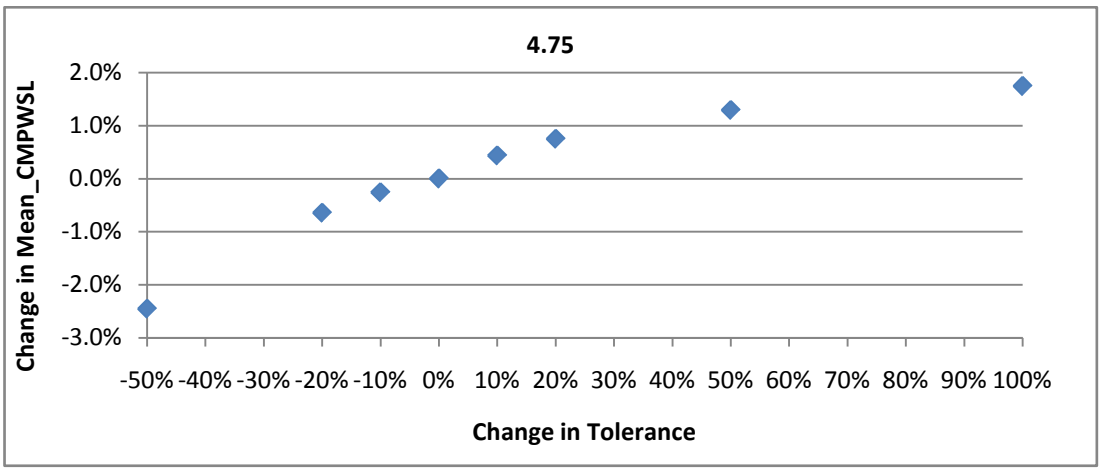

FIGURE 5.10 Effects of Change in 4.75 Specification Tolerance on CMPWSL

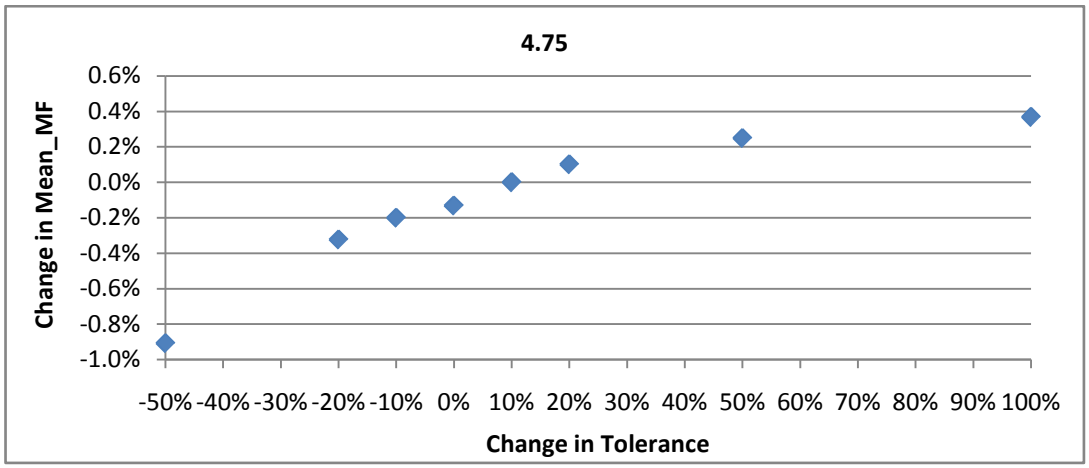

FIGURE 5.11 Effects of Change in 4.75 Specification Tolerance on MF

Due to the heavy relative weight of the AC content in calculating the CMPWSL the analysis shows the change in AC content tolerance has the most significant effect on MF. It can also be observed that MF of 100% is never achieved even though drastic reduction in specification tolerances was considered for any of the four mix parameters (Tables 5.3 through 5.6).

5.1.3 Population Characteristics and Effects on CMPSWL and MF

The population characteristics for each mix parameter (AC content and percent passing 0.075, 2.36, 4.75mm) were next used to evaluate the CMPSWL and MF for each mixture type, at the long term. The results are shown in Figure 5.12. It can be observed that under pay equation 5.1 with a maximum cap (i.e., max 100% pay for 90% PWL), the contractor over the long run can never achieve a pay factor of 100% even when producing at or above 90 CMPSWL. While, for gap graded and high polished mixtures a relatively high MF is achieved, at the long run, for the remaining mixtures the maximum CMPWSL is about 85% which correspond to an MF of 97.5% or less.

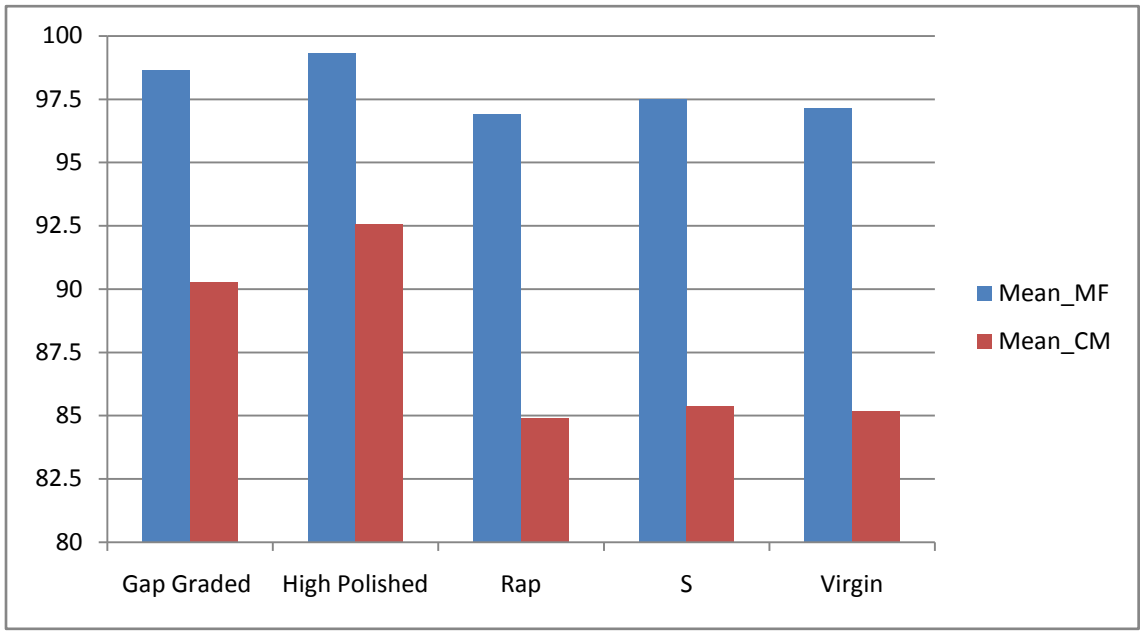

FIGURE 5.12 CMPSWL and MF for Different Mixtures Using Pay Equation 5.1

5.2 Analysis Based on MDSHA Current Specification (with Bonus Provision)

The same analysis as in the previous section was conducted with the pay factor equation 5.2 and the revised tolerances of the new 2008 specification. Under this new pay factor equation, the contractor has the opportunity to achieve a 5% incentive if CMPWSL exceeds 90%.

$$\begin{cases} MF = 0.55 + 0.5CMPWSL \\ if\ CMPWSL < 40\%\ MF = 0 \end{cases}$$ **EQUATION 5.2**

The Composite Mixture PWSL (CMPWSL) is calculated by:

$$CMPWSL = \frac{f1\ PWSL1 + f2\ PWSL2 + f3\ PWSL3 + f4\ PWSL4}{\Sigma f}$$ **EQUATION 5.3**

where:

PWSL1 = asphalt content

PWSL2 = aggregate passing 4.75mm / # 4 sieve

PWSL3 = aggregate passing 2.36 mm / # 8 sieve

PWSL4 = aggregate passing 0.075 mm / # 200 sieve

f1 = asphalt content = 62

f2 = aggregate passing 4.75mm / # 4 sieve=7

f3= aggregate passing 2.36 mm / # 8 sieve =7

f4= aggregate passing 0.075 mm / # 200 sieve=24

5.2.1 Reducing Asphalt Content Variability

As in the previous analysis, the goal was to examine how a reduction in AC variability will affect the average MF while holding the variability of all other parameters (percent passing 0.075, 2.36 and 4.75mm) constant at the population characteristics. The standard deviation of AC was set at 75%, 50% and 25% of the population; the results are shown in Figure 5.13. As it can be seen from this figure, a contractor that is able to produce an HMA mixture with 75% lower variability (0.25 SD/SD_{pop}) than the current QA population variability can increase MF from 98% to about 101% .

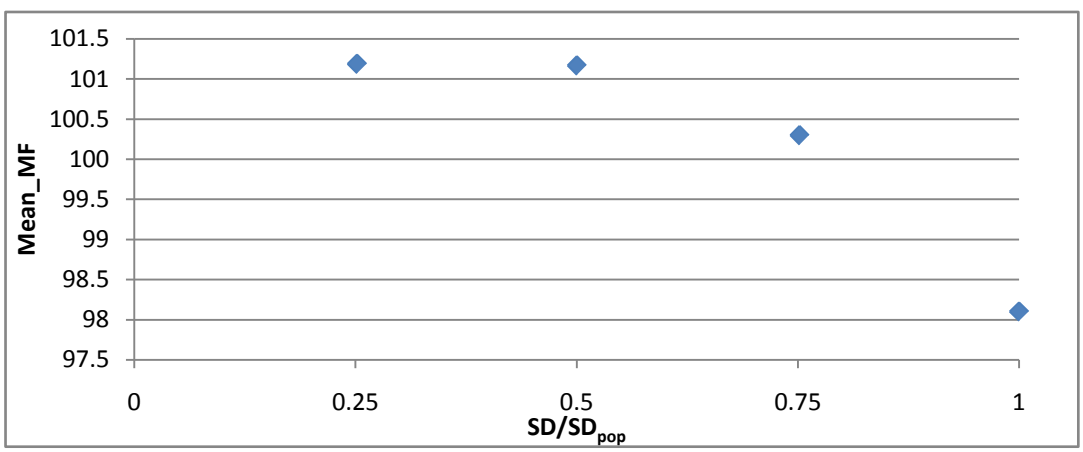

FIGURE 5.13 Effect of Reduction in AC Content Variability on MF

5.2.2 Modifying Specification Tolerances

The effects of changing specification limits (tolerances) on the average MF were examined by using the revised pay equation with the bonus provision. Based on the current specifications, the tolerance for AC is ±0.5%. All other tolerances were kept constant and the AC tolerance was changed for the spec in question. The results are shown in Table 5.7 and Figures 5.14. A change in the tolerance of AC content of about 20% will result in a change of 4% CMPWSL and 1.6% in MF.

TABLE 5.7 Effects of Change in AC Specification Tolerance and Impact on MF

AC_Tol	%Change	Mean_CM	Mean_MF	% Change CM	% Change MF
1	100%	92.4	101.2	7%	3.1%
0.75	50%	91.5	100.8	6%	2.7%
0.6	20%	89.3	99.7	4%	1.6%
0.55	10%	88.0	99.0	2%	0.9%
0.5	0%	86.2	98.1	0%	0.0%
0.45	-10%	83.6	96.8	-3%	-1.3%
0.4	-20%	80.7	95.4	-6%	-2.8%
0.25	-50%	66.8	88.4	-23%	-10.0%

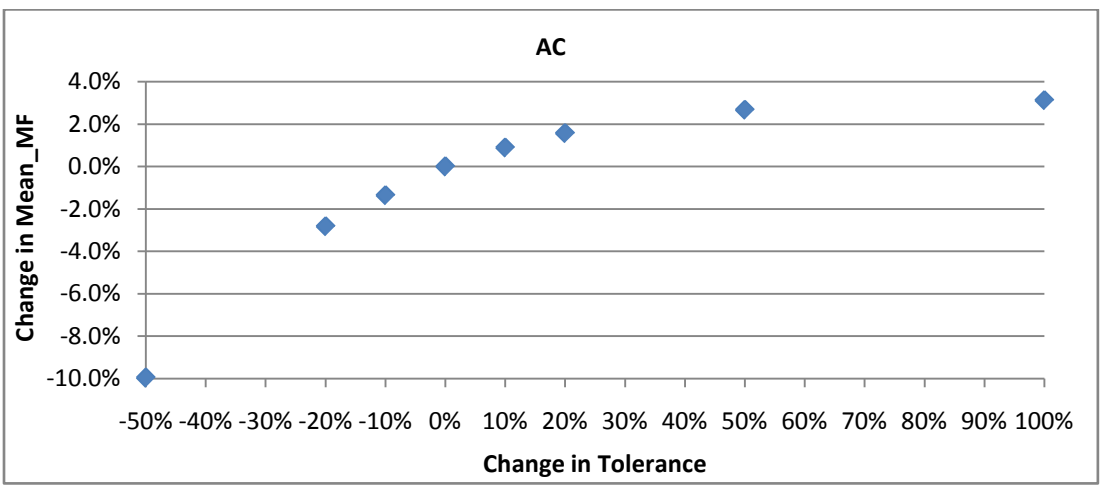

FIGURE 5.14 Effects of Change in AC Specification Tolerance on MF

Similarly, the effect of changing the 0.075 percent passing specification tolerance was also examined. The current specification has a tolerance of ±2%. The results are shown in Table 5.8 and Figure 5.15.

TABLE 5.8 Effects of Change in 0.075 Specification Tolerance and Impact on MF

0.075_Tol	%Change	Mean_CM	Mean_MF	% Change CM	% Change MF
4	100%	90.8	100.4	5.5%	2.4%
3	50%	89.8	99.9	4.3%	1.9%
2.4	20%	88.1	99.1	2.4%	1.0%
2.2	10%	87.2	98.6	1.3%	0.5%
2	0%	86.1	98.0	0.0%	0.0%
1.8	-10%	84.9	97.5	-1.3%	-0.6%
1.6	-20%	83.4	96.7	-3.1%	-1.4%
1	-50%	78.0	94.0	-9.4%	-4.1%

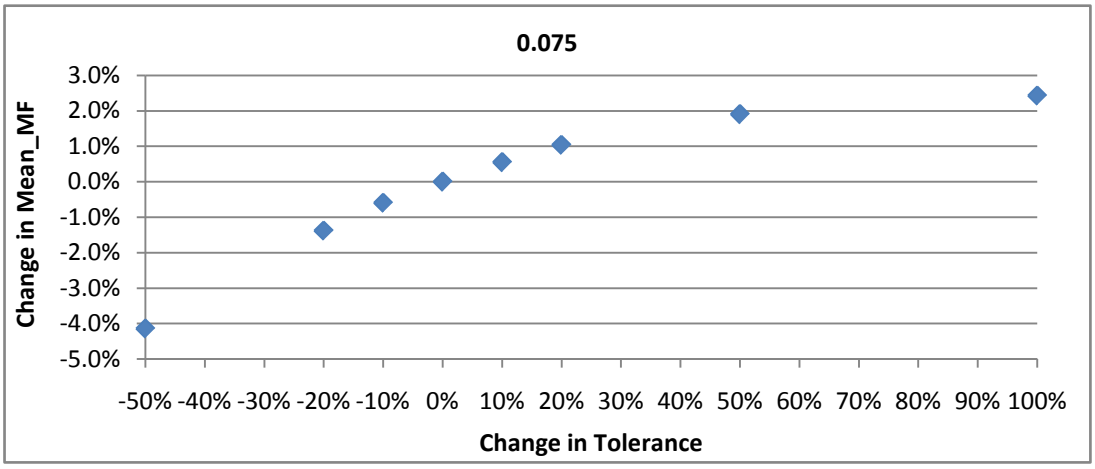

FIGURE 5.15 Effects of Change in 0.075 Specification Tolerance on MF

The effect of changing the 2.36 percent passing specification tolerance was also examined with the bonus provision. The current specifications has a tolerance of ±5%. The results are shown in Table 5.9 and Figure 5.16.

TABLE 5.9 Effects of Change in 2.36 Specification Tolerance on MF

2.36_Tol	%Change	Mean_CM	Mean_MF	% Change CM	% Change MF
10	100%	87.4	98.7	1.48%	0.57%
7.5	50%	87.1	98.5	1.13%	0.41%
6	20%	86.7	98.3	0.69%	0.22%
5.5	10%	86.3	98.2	0.26%	0.03%
5	0%	86.1	98.0	-0.01%	-0.09%
4.5	-10%	85.7	97.8	-0.48%	-0.29%
4	-20%	85.3	97.6	-0.92%	-0.49%
2.5	-50%	83.9	96.9	-2.57%	-1.21%

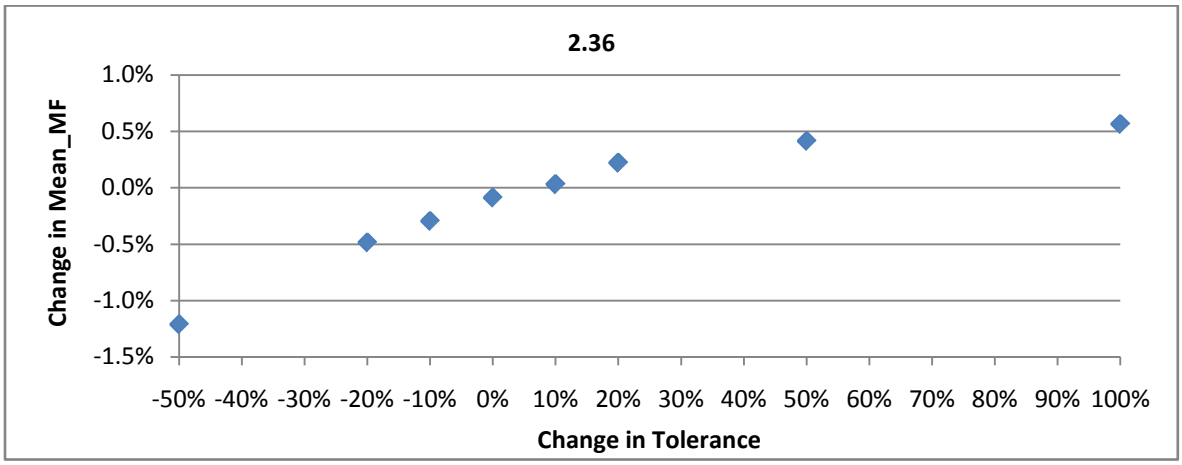

FIGURE 5.16 Effects of Change in 2.36 Specification Tolerance on MF

Finally, the effect of changing the 4.75 percent passing specification tolerance was examined. The current specifications has a tolerance of ±7%. The results are shown in Table 5.10 and Figure 5.17.

TABLE 5.10 Effects of Change in 4.75 Specification Tolerance on MF

4.75_Tol	%Change	Mean_CM	Mean_MF	% Change CM	% Change MF
14	100%	87.5	98.8	1.7%	1%
10.5	50%	87.2	98.6	1.3%	0.5%
8.4	20%	86.6	98.3	0.7%	0.2%
7.7	10%	86.2	98.1	0.2%	0.0%
7	0%	86.1	98.0	0.0%	-0.1%
6.3	-10%	85.8	97.9	-0.3%	-0.2%
5.6	-20%	85.2	97.6	-1.0%	-0.5%
3.5	-50%	83.9	97.0	-2.5%	-1%

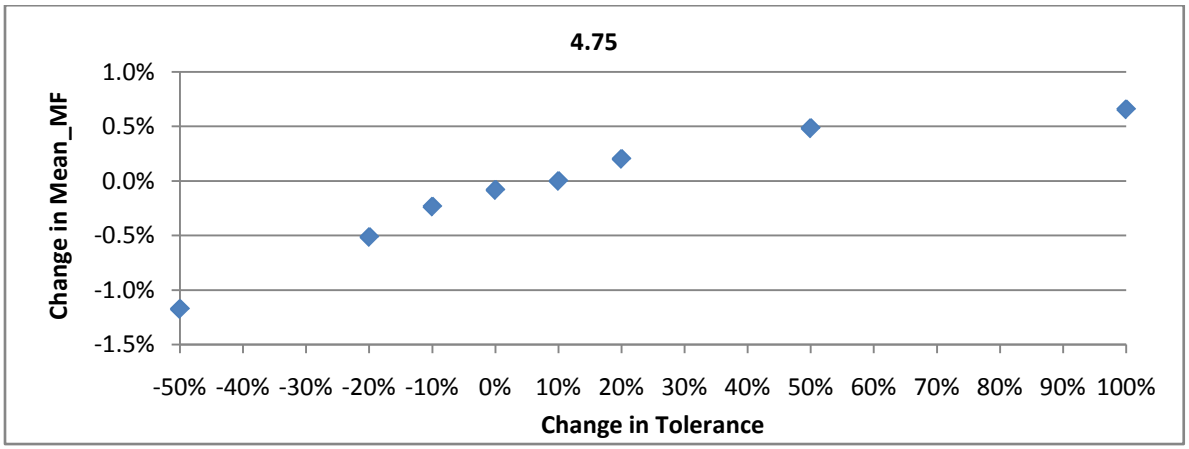

FIGURE 5.17 Effects of Change in 4.75 Specification Tolerance on MF

Due to the heavy relative weight of the AC content in calculating the CMPWSL the analysis shows the change in AC content tolerance has the most significant effect on MF. It can also be observed that with the bonus provision of the new specification an MF above 100% is achievable for certain conditions.

5.2.3 Population Characteristics and Effects on CMPSWL and MF

The population characteristics for each mix parameter (AC content and percent passing 0.075, 2.36, 4.75mm sieves) were used next to evaluate the CMPSWL and MF for each mixture type at the long term using equation 5.2 with bonus pay provision. The results are shown in Figure 5.18. It can be observed that using the bonus provision the contractor can achieve on the average a pay factor of 100% when producing at 90 CMPWSL. While for gap graded and high polished mixtures an MF above 100% is achieved for the remaining mixtures an MF of 97.5% is achieved.

5.3 Other Analysis

The variability in the population characteristics was then compared to the variability of the various plants producing HMA mixtures in MD. The results of this analysis for the asphalt content of the virgin mixtures are shown in Figure 5.19. Both median and mean values are shown as well. While the majority of the plants produce below the average value, the plants with higher variability affect the overall variability since they represent high production HMA plants.

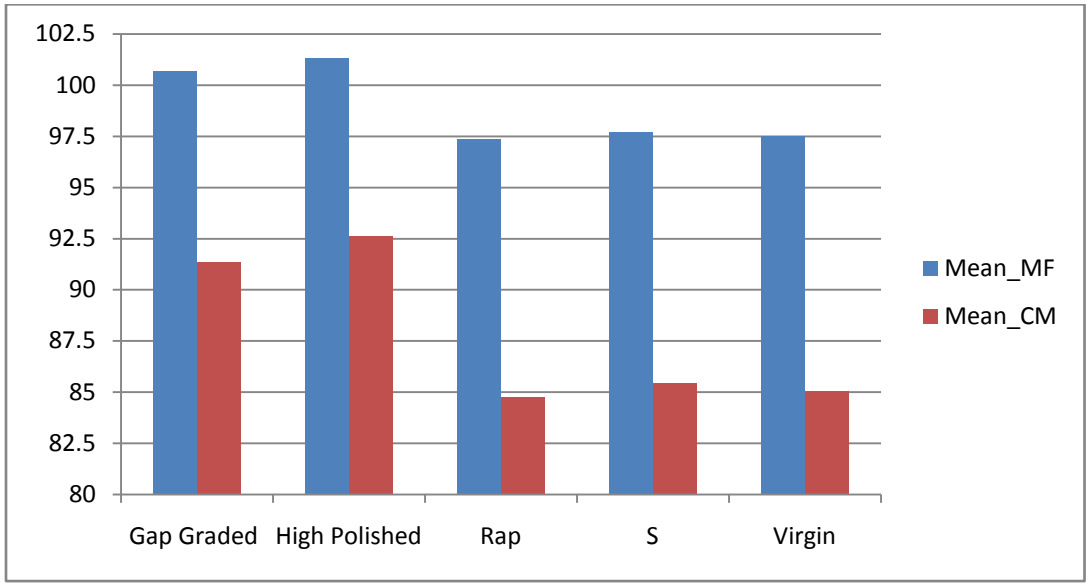

FIGURE 5.18 CMPSWL and MF for Different Mixtures Using Bonus Provision

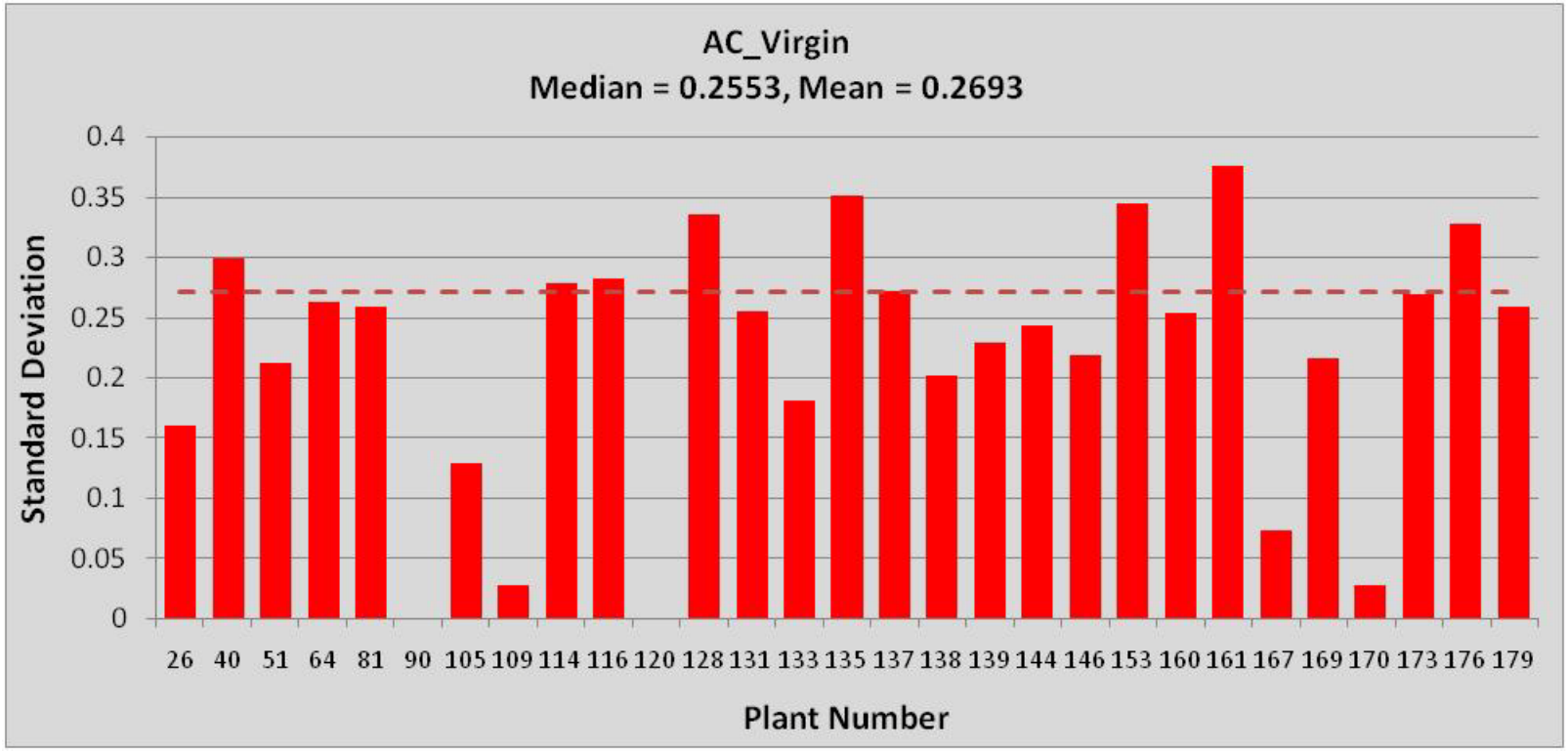

FIGURE 5.19 Variability in Asphalt Content by Various Plants in Maryland

CHAPTER 6 PAY FACTOR ANALYSIS

6.1 Dense Graded HMA

6.1.1 Mixture Expected Pay Analysis

In order to develop the EP Curves for the acceptance plan with payment adjustments the population characteristics were used for the four mix parameters, Table 6.1. The population distributions were then shifted at levels producing different PWL values. Figures 6.1 through 6.4 show the current location of the populations for each one of the four mix parameters in relation to the specification tolerances (USL, LSL).

Schematically, the populations of the four mix parameters are then shifted at AQL and RQL so that 90% and 40% of the population is within tolerances (Figures 6.5 through 6.14). To notice that in some of the cases (0.075, 2.36, and 4.75) 90PWL cannot be achieved due to the distribution variability and width of the tolerances. The EP Curves were thus generated for different pay factor levels (0.075, 0.80, 0.90, 1.00 and 1.04).

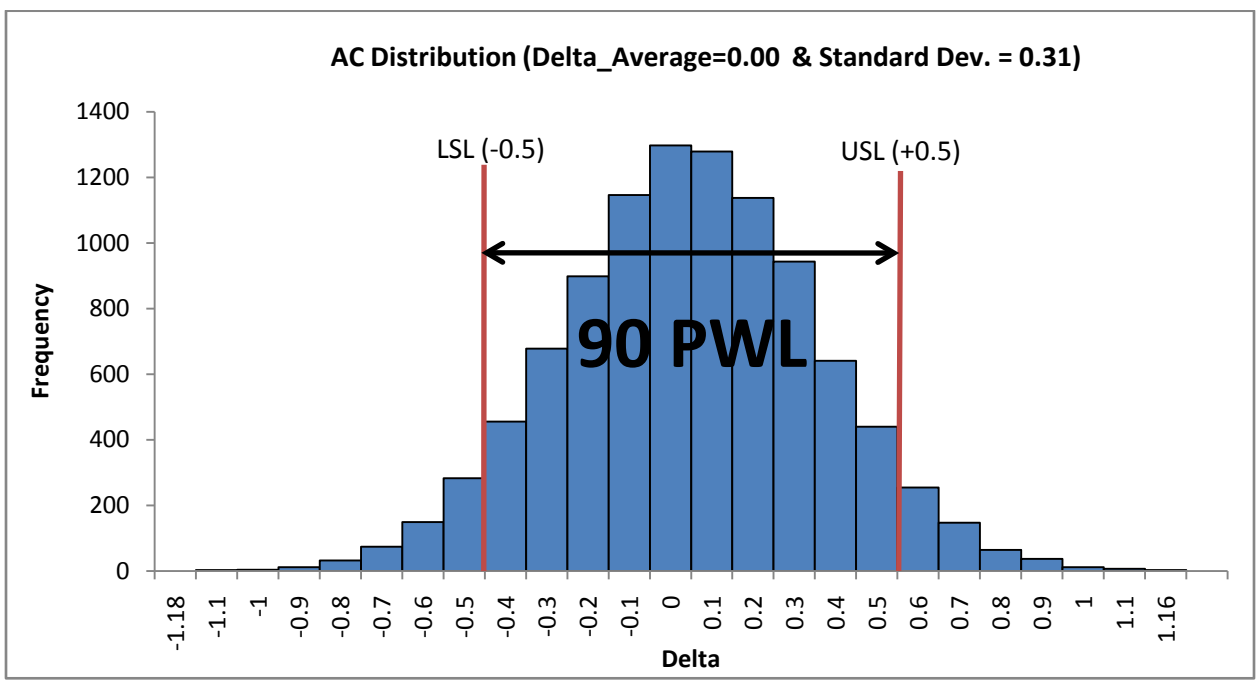

FIGURE 6.1 Distribution of Asphalt Content Population and the Tolerances

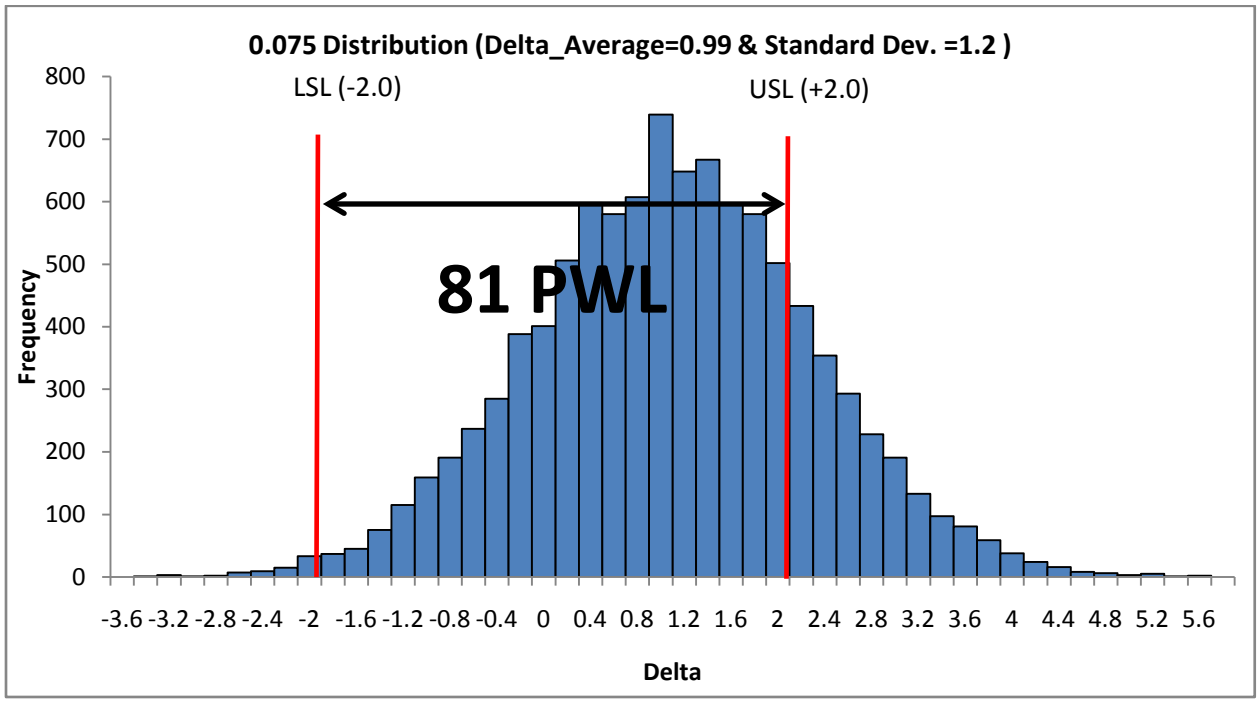

FIGURE 6.2 Distribution of Passing 0.075mm Population and the Tolerances

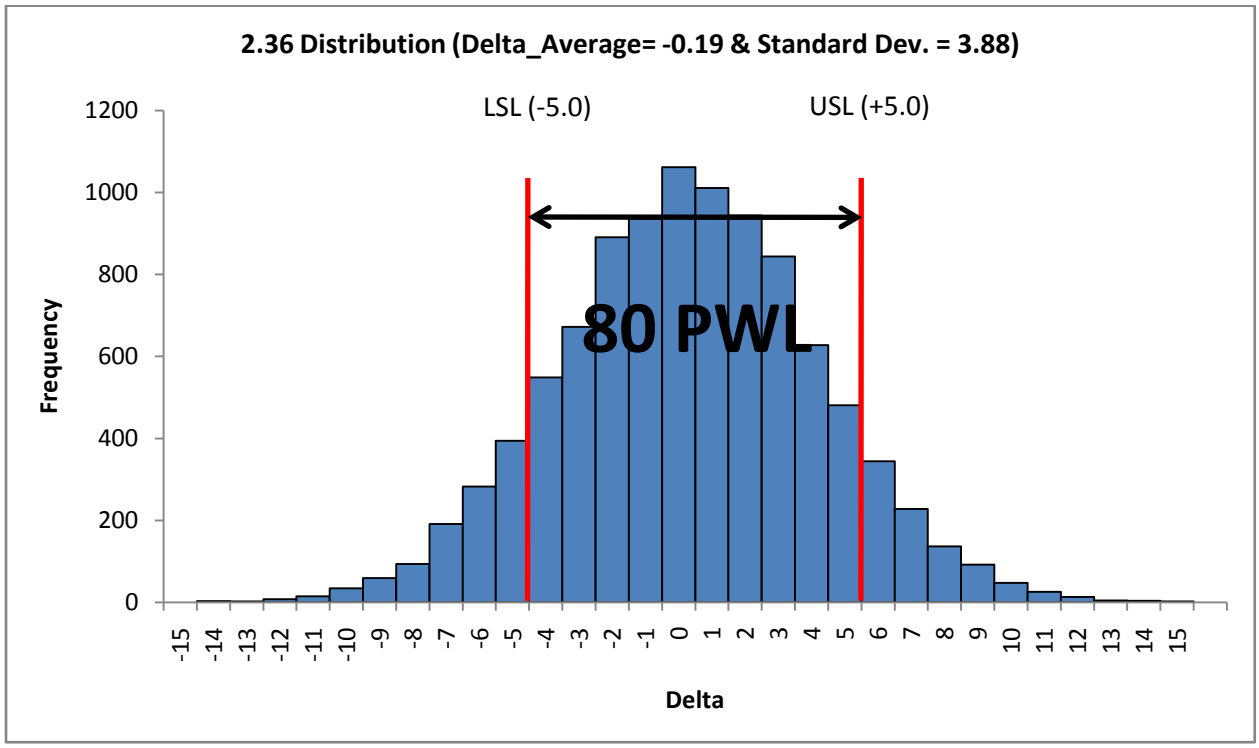

FIGURE 6.3 Distribution of Passing 2.36mm Population and the Tolerances

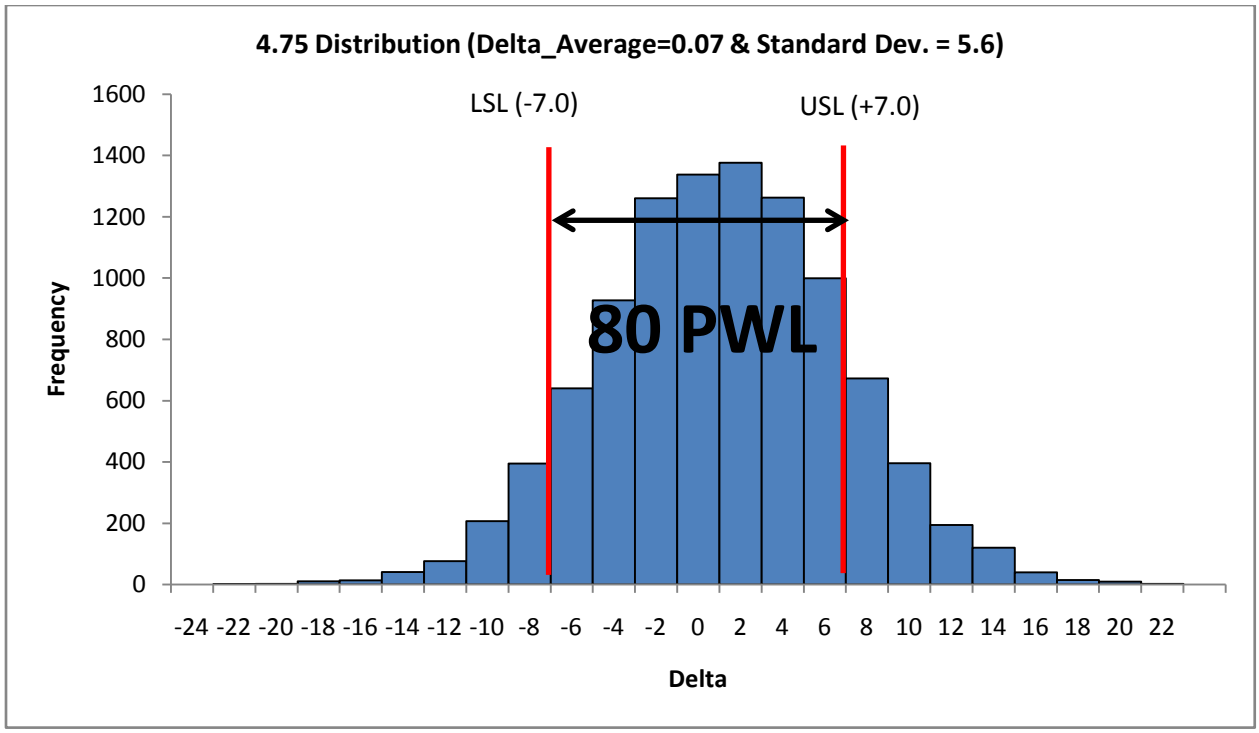

FIGURE 6.4 Distribution of Passing 4.75mm Population and the Tolerances

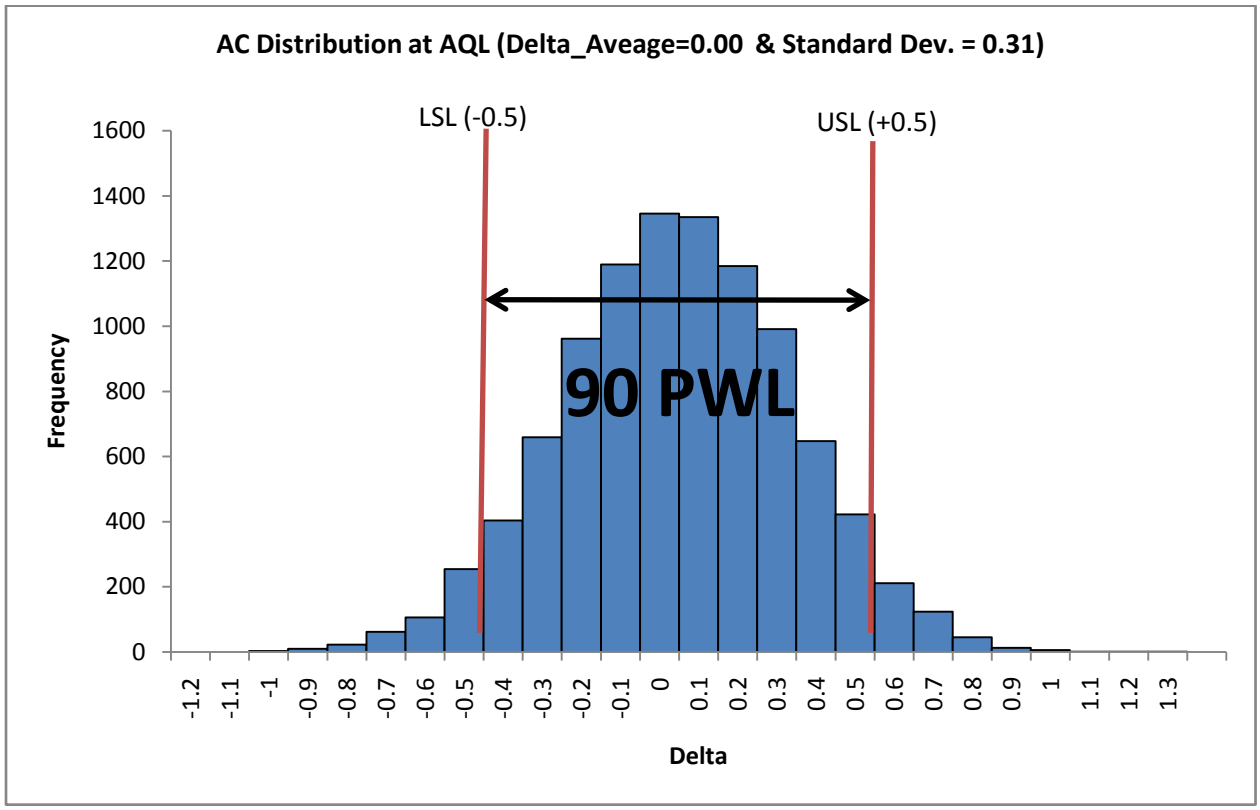

FIGURE 6.5 Distribution of Asphalt Content at AQL

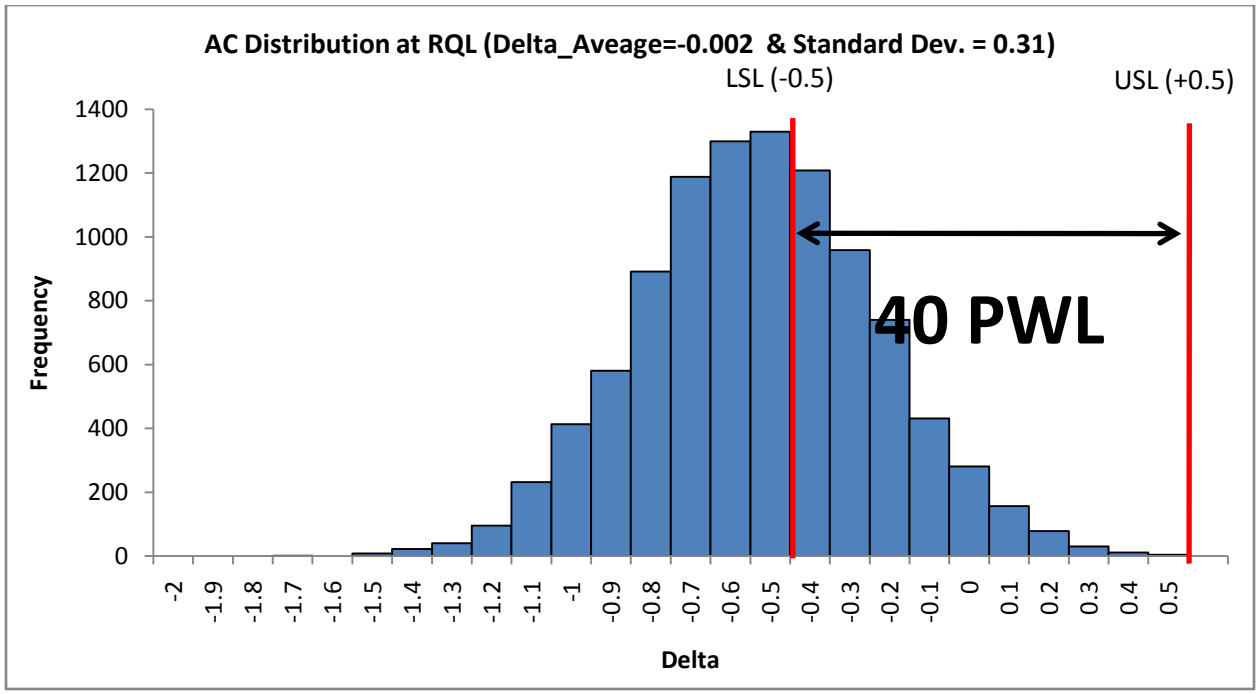

FIGURE 6.6 Distribution of Asphalt Content at RQL

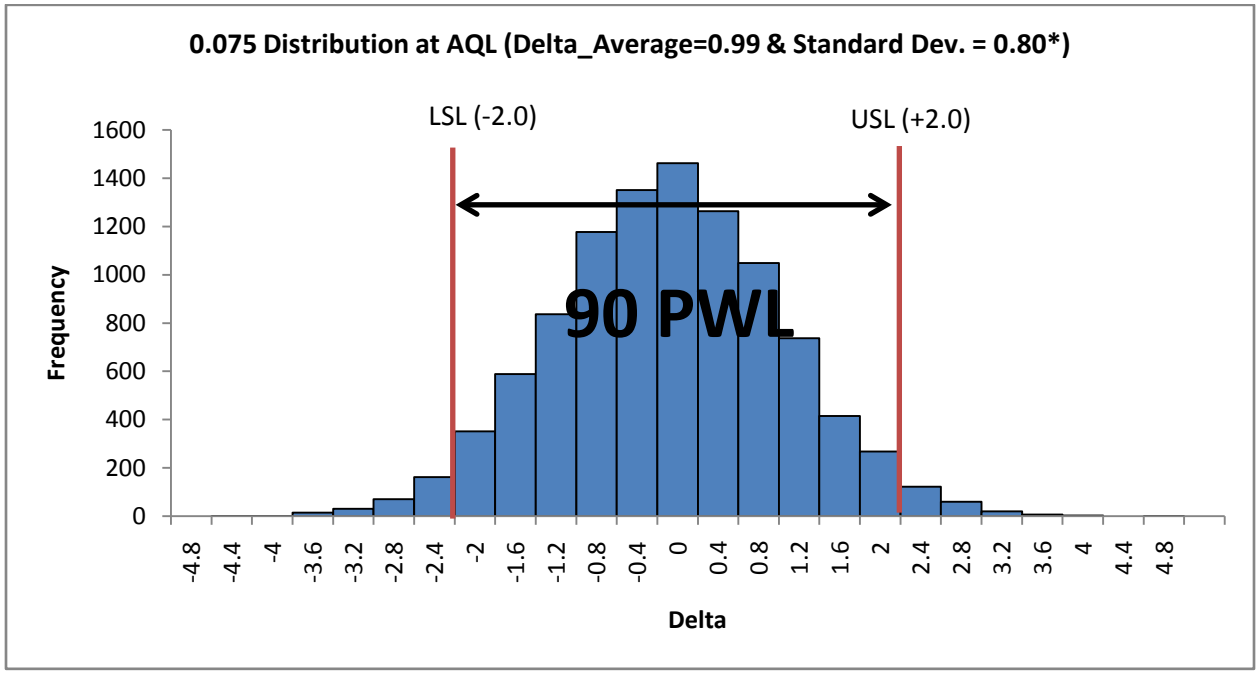

FIGURE 6.7 Distribution of Passing 0.075mm at AQL

***Note: In order to achieve 90PWL the standard deviation was reduced by 33%**

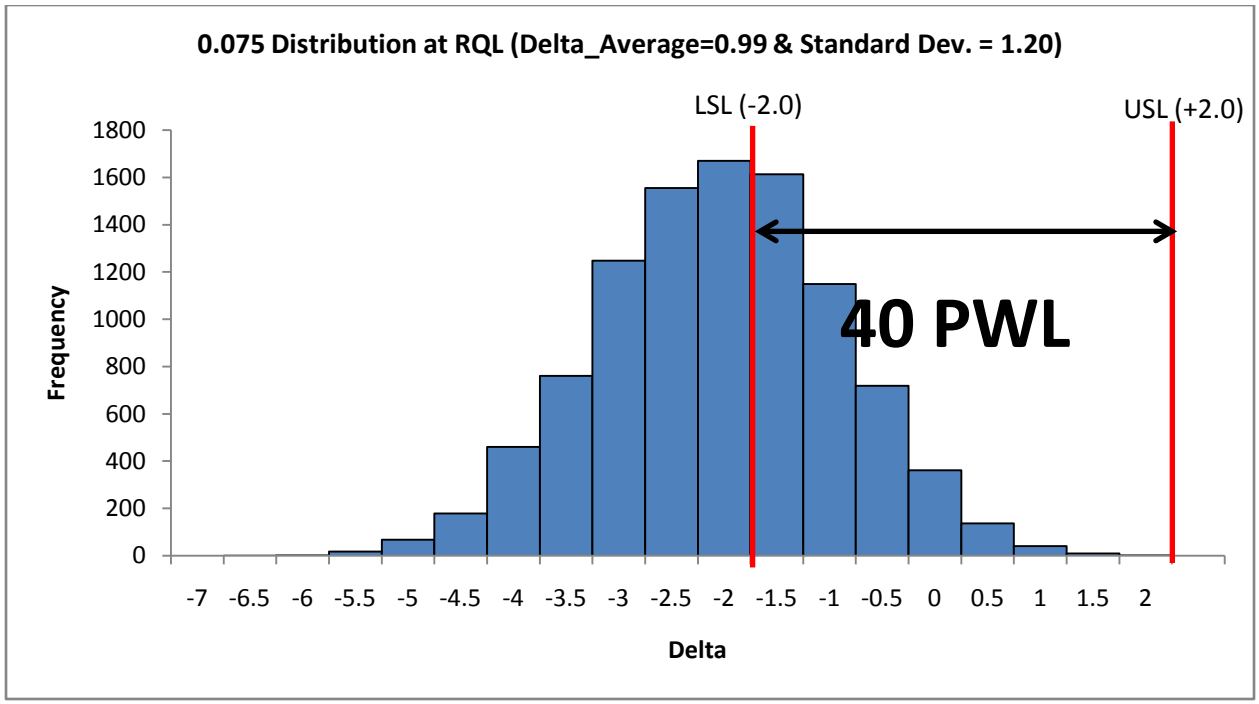

FIGURE 6.8 Distribution of Passing 0.075mm at RQL

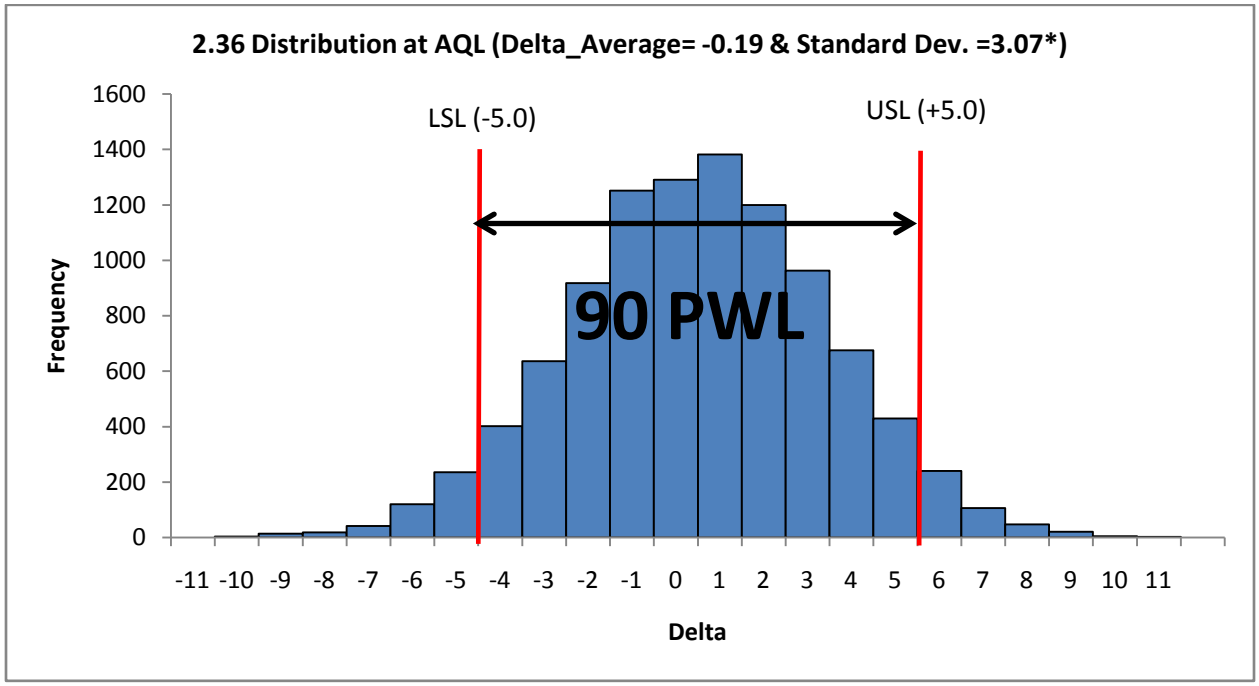

FIGURE 6.9 Distribution of Passing 2.36mm at AQL

***Note: In order to achieve 90PWL the standard deviation was reduced by 21%**

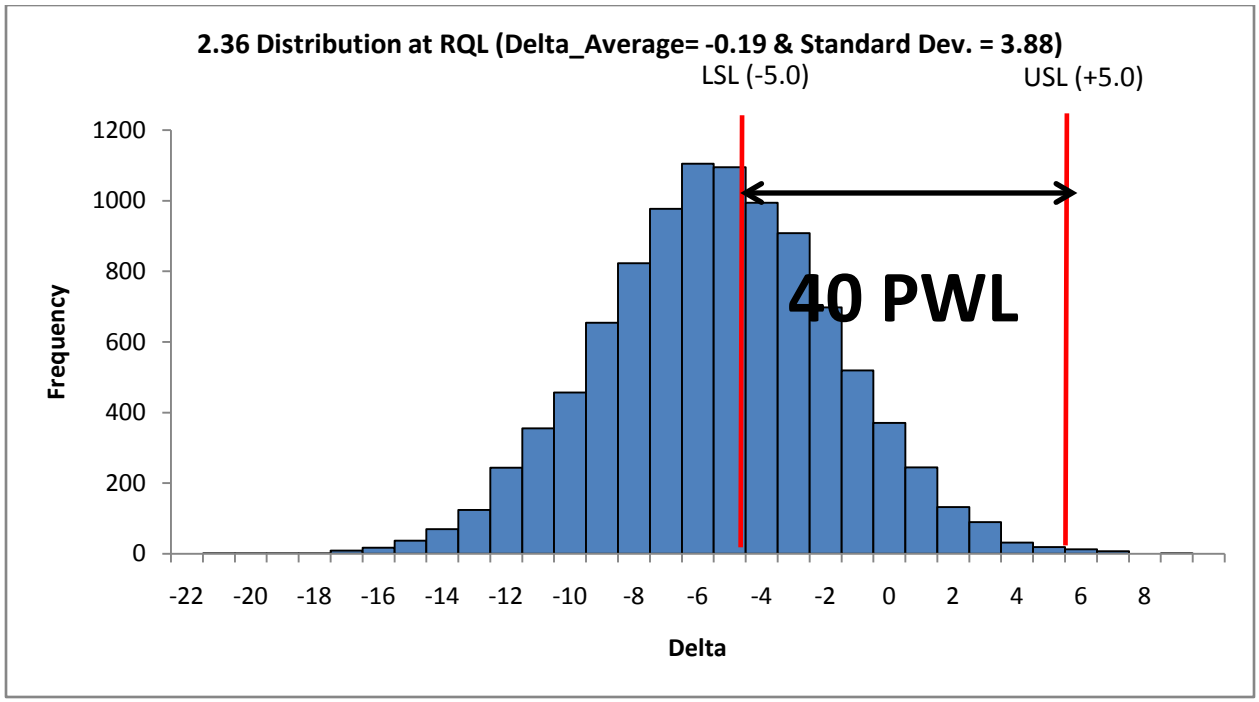

FIGURE 6.10 Distribution of Passing 2.36mm at RQL

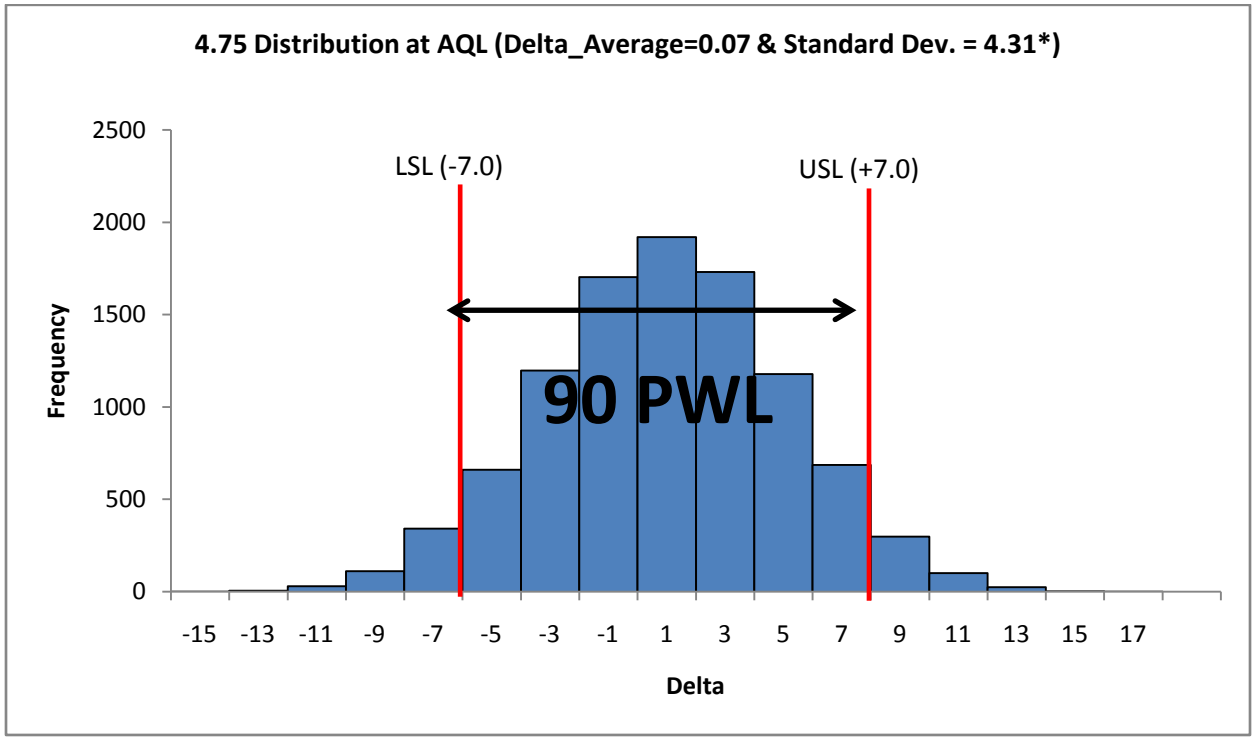

FIGURE 6.11 Distribution of Passing 4.75mm at AQL

***Note: In order to achieve 90PWL the standard deviation was reduced by 23%**

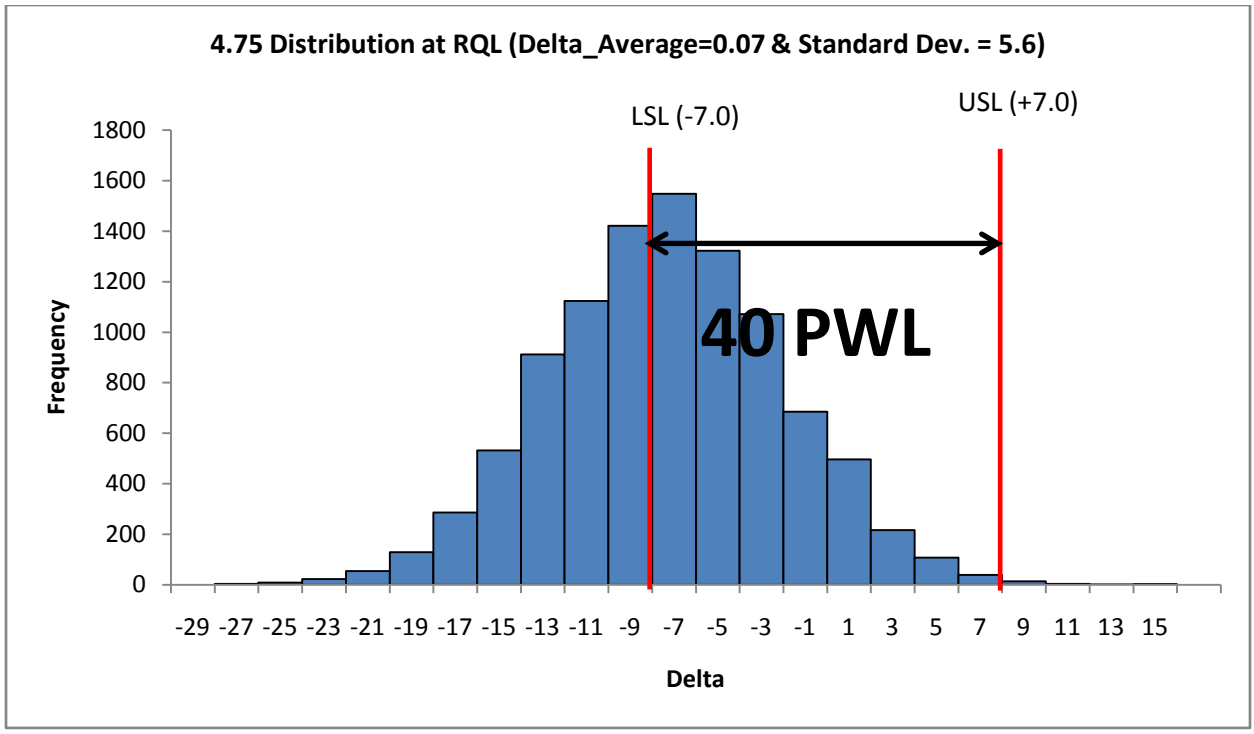

FIGURE 6.12 Distribution of Passing 4.75mm at RQL

Figure 6.13 shows the probability of receiving ≥PF (y-axis) in relation to the quality level CMPWL (x-axis), while Table 6.2 summarizes the values obtained at each CMPWSL from the simulation analysis.

As it can be seen from Table 6.2, when the population standard deviations for the four mixture parameters are used the highest achievable CMPWSL is 88.7. Thus, for values above this level the probability values were interpolated. Furthermore, the simulation analysis have shown that the probability of receiving a PF< 1 when producing at AQL (90CMPWL) is about 40%, while the probability of receiving a PF≥ 1 when producing at RQL (40CMPWL) is 0%. Similarly the expected pay at any other level of CMPWSL, or the probability of receiving different levels of PF at AQL and RQL can be estimated from these results.

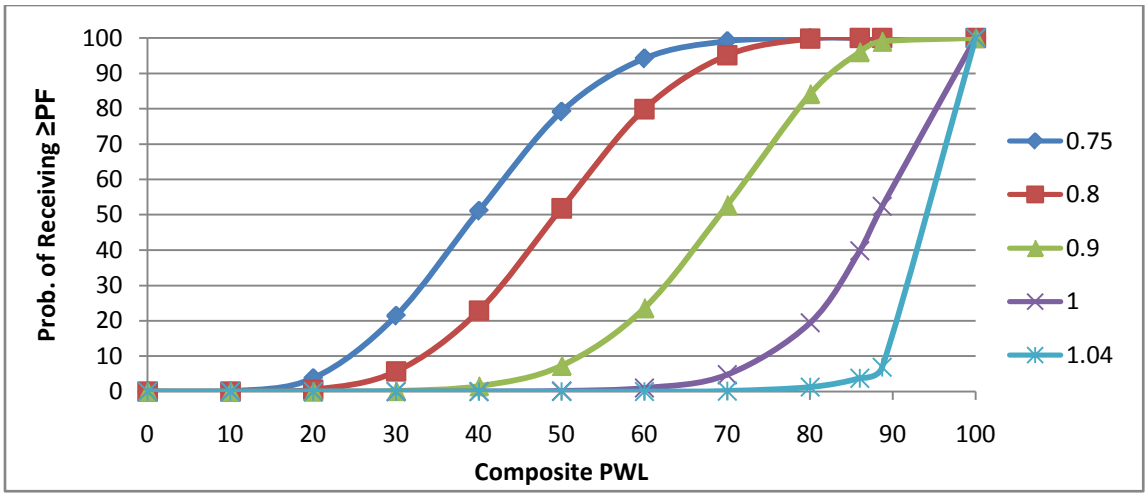

FIGURE 6.13 EP Curves with Expected PF Using Population Characteristics

TABLE 6.1 Standard Deviation of Different Properties

Property	0.075	2.36	4.75	AC
Std. Dev.	1.2	3.88	5.6	0.31

TABLE 6.2 Probability of Receiving ≥PF at Different CMPWL with Population Characteristics

CMPWL	**Prob of Receiving ≥PF**				
	0.75	**0.8**	**0.9**	**1**	**1.04**
0	0	0	0	0	0
10	0.1	0	0	0	0
20	3.81	0.55	0.01	0	0
30	21.47	5.72	0.17	0	0
40	51.11	22.9	1.57	0.01	0
50	79.19	51.82	7.3	0.13	0
60	94.14	79.86	23.57	1	0.02
70	99.04	95.08	52.71	4.76	0.14
80	99.98	99.78	84.15	19.43	1.25
86	100	100	96.02	39.82	3.77
88.7	100	100	98.95	52.41	6.88
100	100	100	100	100	100

Note1: simulation at 10000 iterations for each CMPWL
Note2: assumed values at 100PWL since only 88.7% of the data fits within spec tolerances

Figures 6.14 and 6.15 show the CMPWL and pay factor distribution. At the long run the average pay factor for a 88.7CMPWL is equal to 0.99, while for RQL the average pay factor is 0.40. Table 6.3 includes the expected pay - EP (PF at the long run) calculations when the population is shifted within the specification tolerances to produce different levels of CMPWSL.

TABLE 6.3 Expected Payment in relation to CMPWL with Population Characteristics*

CMPWL	EP
100.0	1.05
90.0	1.00
88.7	0.99
80.0	0.95
70.0	0.89
60.0	0.81
50.0	0.65
40.0	0.41

Note: * The maximum achievable CMPWL with population standard deviation is 88.7; 90CMPWL obtained with population standard deviation reduced by 3.6%; 100CPWL obtained by reducing population standard deviation by 55%.

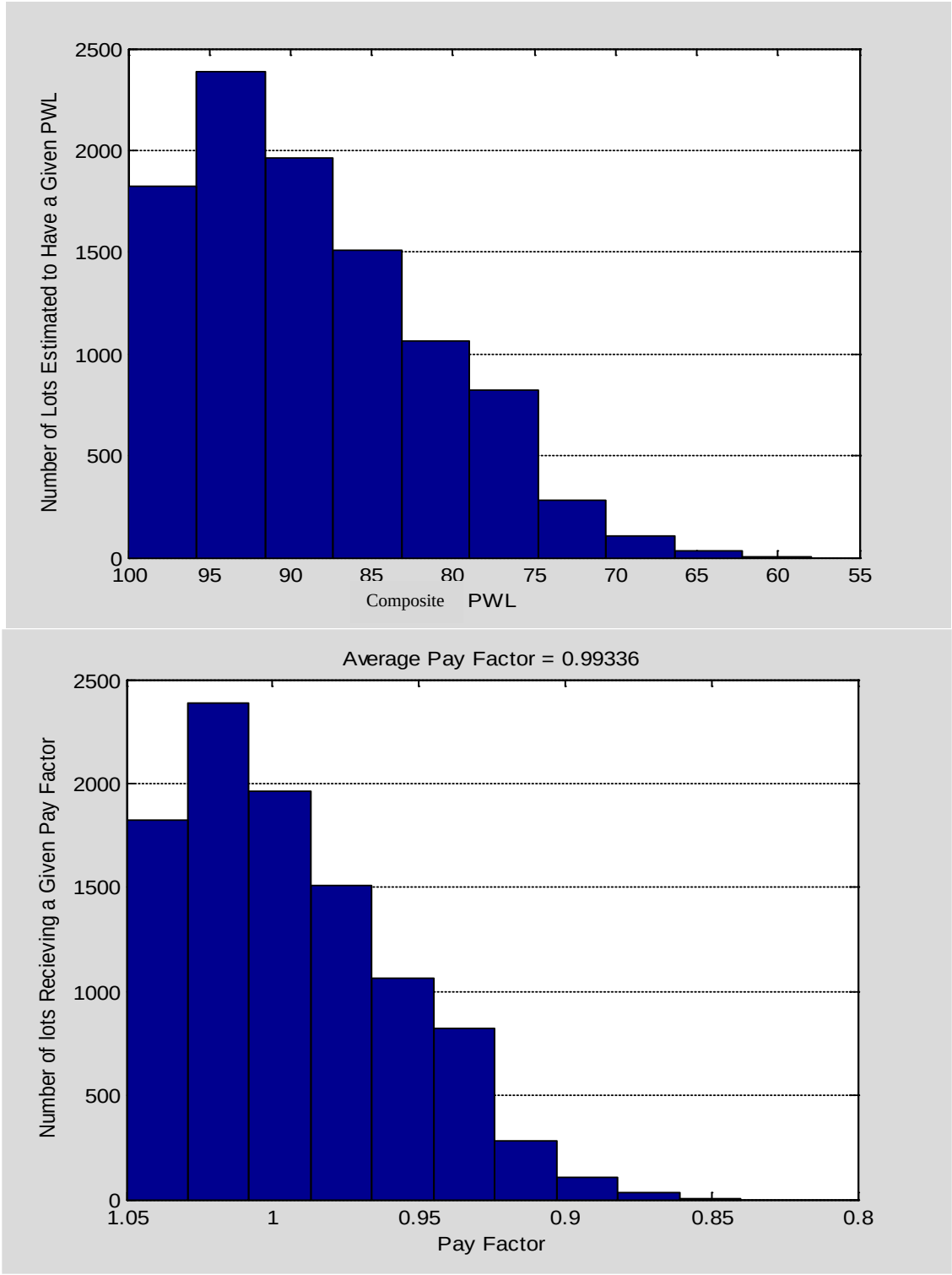

FIGURE 6.14 CMPWL and Pay Factor Distribution for Production "close to" AQL (max CMPWL = 88.7 using population standard deviation)

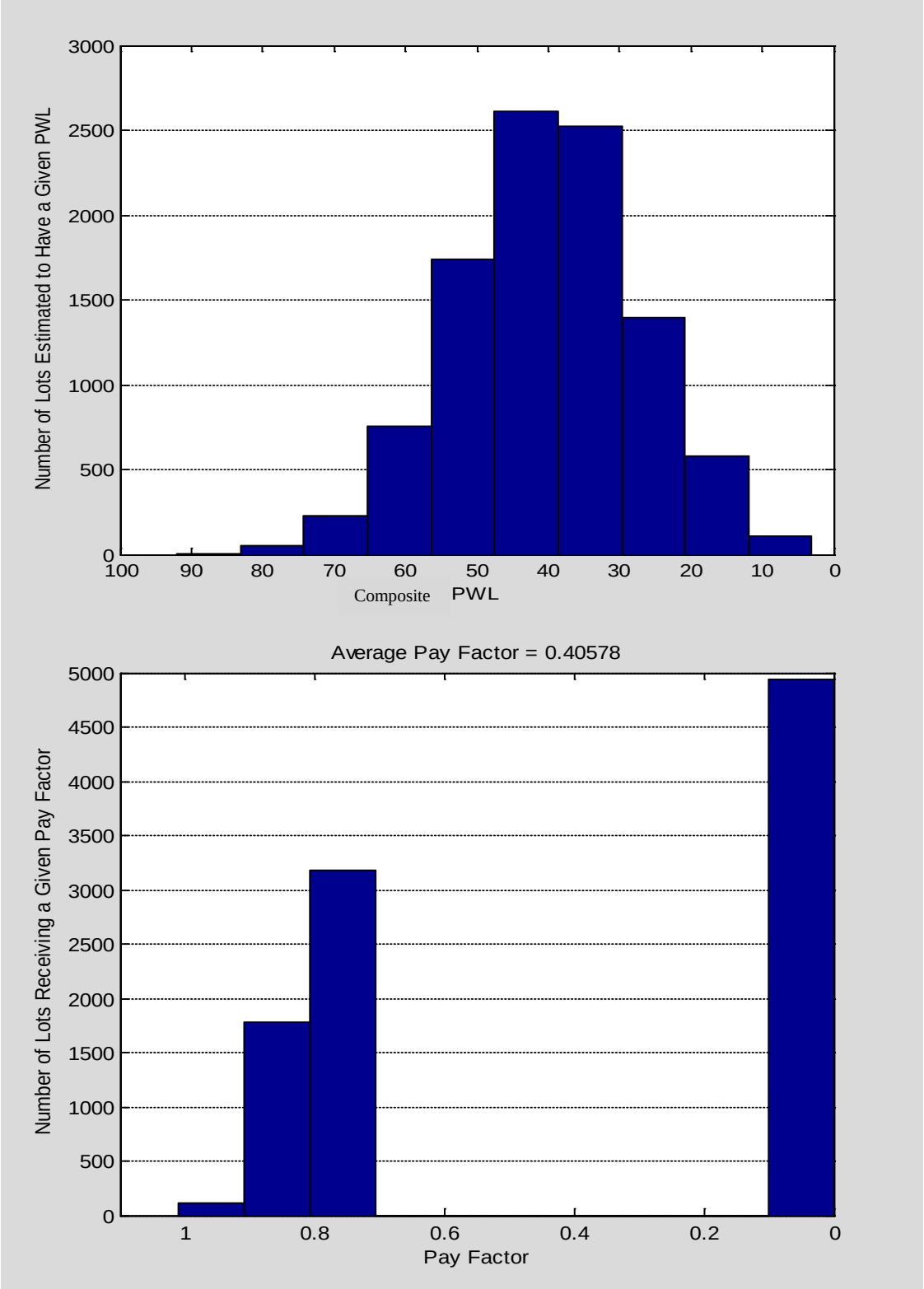

FIGURE 6.15 CMPWL and Pay Factor Distribution for RQL (with population standard deviation)

6.1.2 Improving Production Quality & Potential Modifications in Spec Tolerances

As indicated previously, based on the population characteristics of the four HMA mixture parameters only 88.7% of the data are within the specification tolerances. Thus, in order to achieve, at the long run, a 90CMPWSL (AQL value for MSHA spec) either the mixture production variability has to be reduced (higher homogeneity during production, reducing variability and consequently the population standard deviation), or the specification limits have to be widen (if it is concluded that the existing variability represents the best achievable levels of production). As an example, in the first case reducing the population standard deviations for all four properties by 3.6% (i.e., improving production uniformity) will provide a 90CMPWSL with the current tolerances. The results of the simulation analysis are summarized in Table 6.4 and plotted in Figure 6.16.

As shown from these analyses the probability of receiving a PF< 100% when producing at AQL (90CMPWL) and the probability of receiving a PF≥ 1 when producing at RQL (40CMPWL) remain at the same levels of 40% and 0% respectively.

Figures 6.17 and 6.18 show the CMPWSL and pay factor distribution for these analyses. Similarly to the previous analysis, the average pay factor, at the long run, remains the same (for a 90CMPWL is equal to 1.0, while for RQL the average pay factor is 0.4.

Further analyses have shown that reducing the variance of the population, and/or modifying the specification tolerances, wouldn't affect the above PF parameters at AQL and RQL (these results are reported in the Appendix). Thus, an alternative approach may be required if the agency is interested in modifying the mix property pay factor specifications. In such an approach either the AQL has to be modified and/or the associated PWL - pay schedule equation.

A method was proposed by WSDOT and is reported in the Appendix along with some example analysis.

TABLE 6.4 Probability of Receiving ≥PF at Different PWL by Reducing Population Variability

PWL	Prob of Receiving >=PF				
	0.75	0.8	0.9	1	1.04
0	0	0	0	0	0
10	0.09	0.01	0	0	0
20	3.47	0.53	0	0	0
30	21.9	5.96	0.14	0	0
40	50.22	22.99	1.44	0	0
50	78.78	51.69	7.22	0.14	0
60	94.19	80.05	24.03	0.91	0.03
70	98.96	94.72	52.13	4.74	0.23
80	99.96	99.7	84.53	20.01	1.38
90	100	100	99.43	59.66	10.16
100	100	100	100	100	100

Note1: 10000 iterations at each PWL
Note2: The values at 100PWL are interpolated

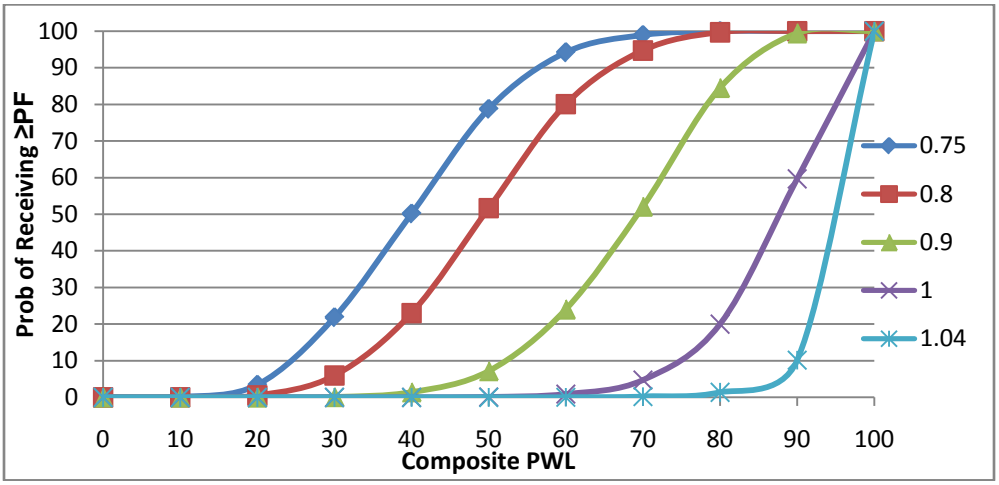

FIGURE 6.16 EP Curves with expected PF Using Reduced Population Variability

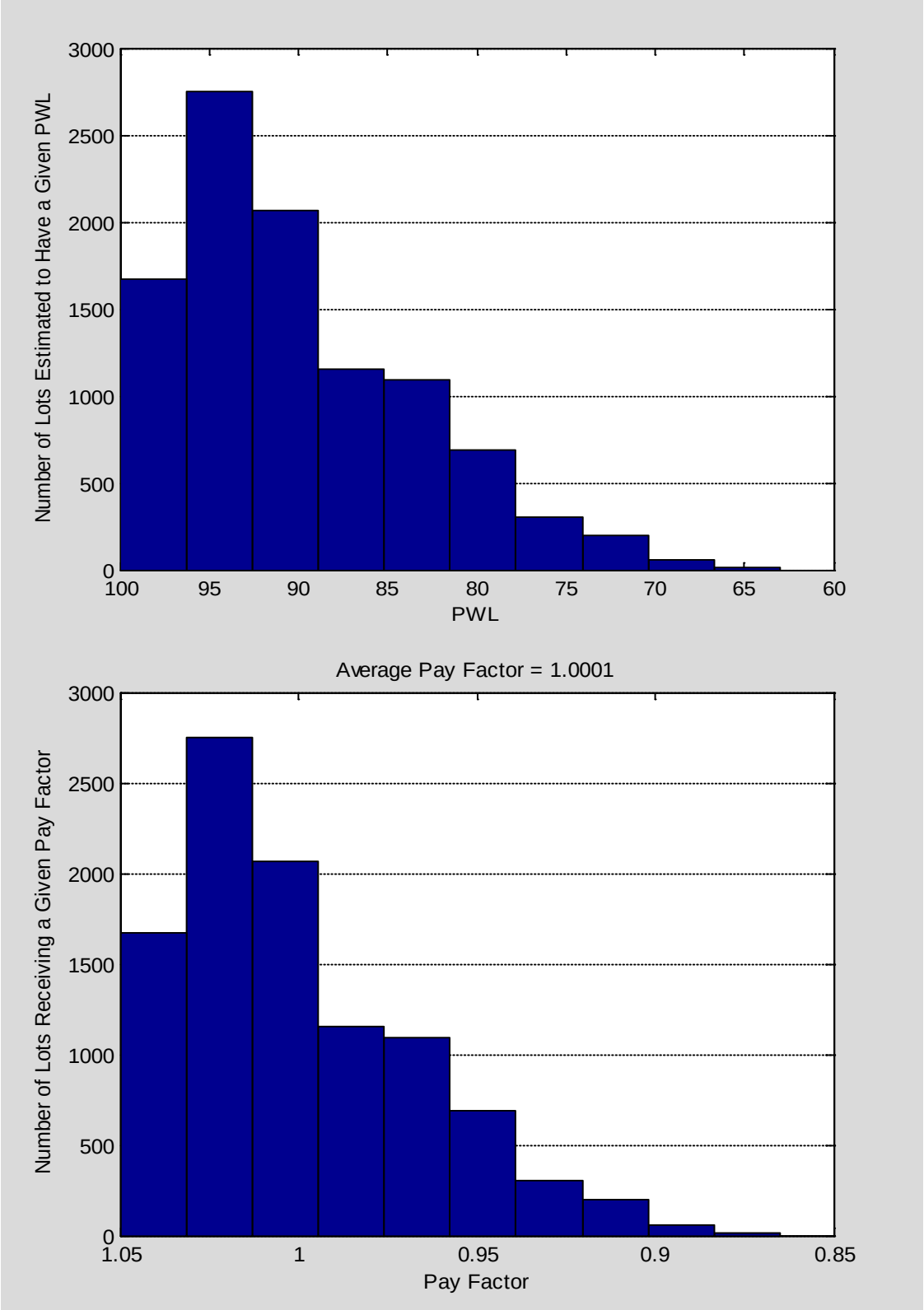

FIGURE 6.17 CMPWL and Pay Factor Distribution for AQL Production with Reduced Population Variability

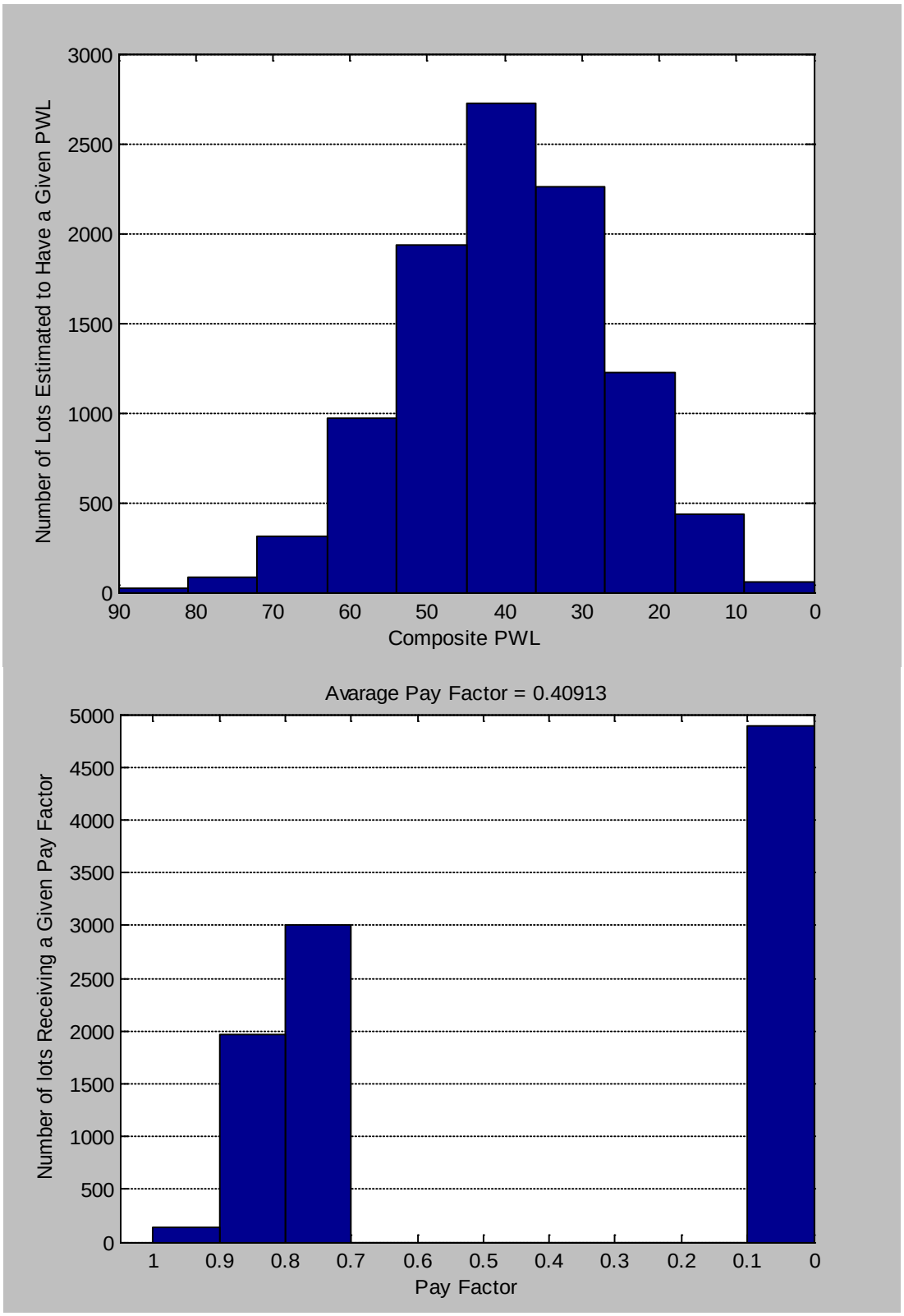

FIGURE 6.18 CMPWL and Pay Factor Distribution for RQL Production with Reduced Population Variability

6.2 Gap Graded HMA

6.2.1 Mixtures Expected Pay Analysis

The same analysis was carried out for the gap graded HMA mixtures. The population characteristics are shown in Table 6.5. Similarly, the population distributions were then shifted at levels producing different PWL values and The OC Curves were thus generated for different pay factor levels (0.75, 0.80, 0.90, 1.00 and 1.04).

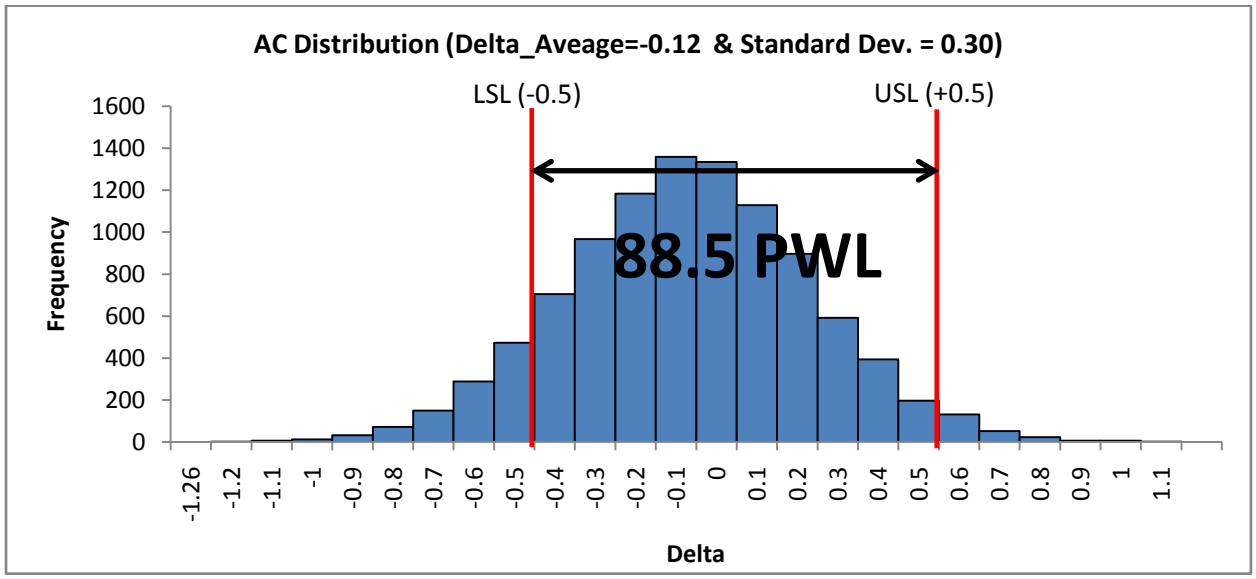

FIGURE 6.19 Distribution of Passing AC Population and the Tolerances

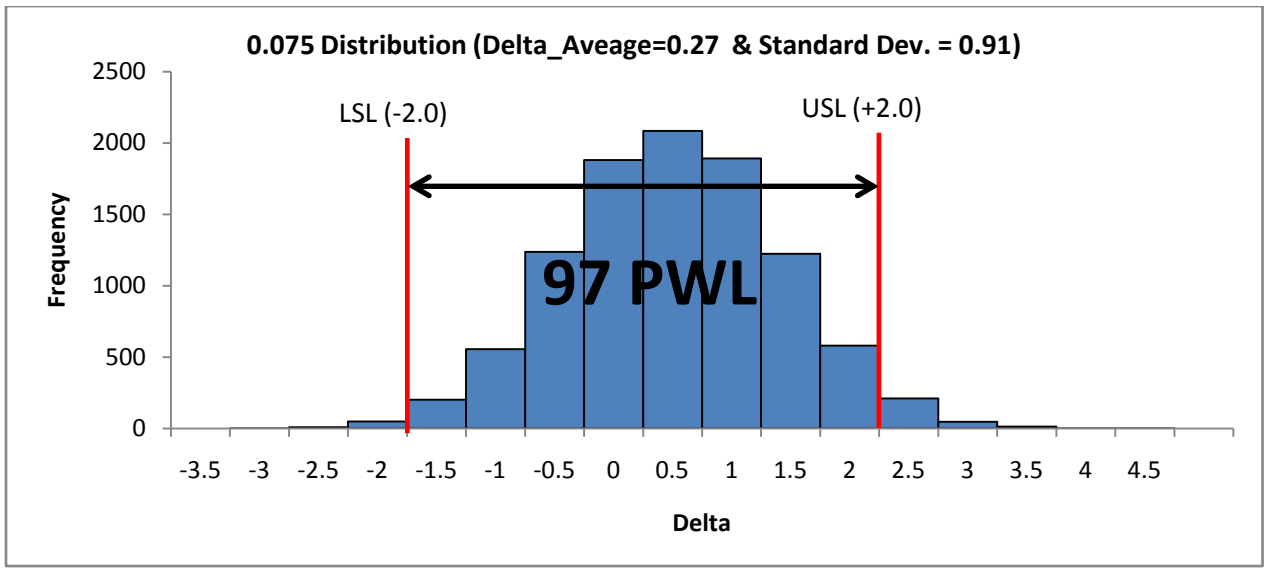

FIGURE 6.20 Distribution of Passing 0.075mm Population and the Tolerances

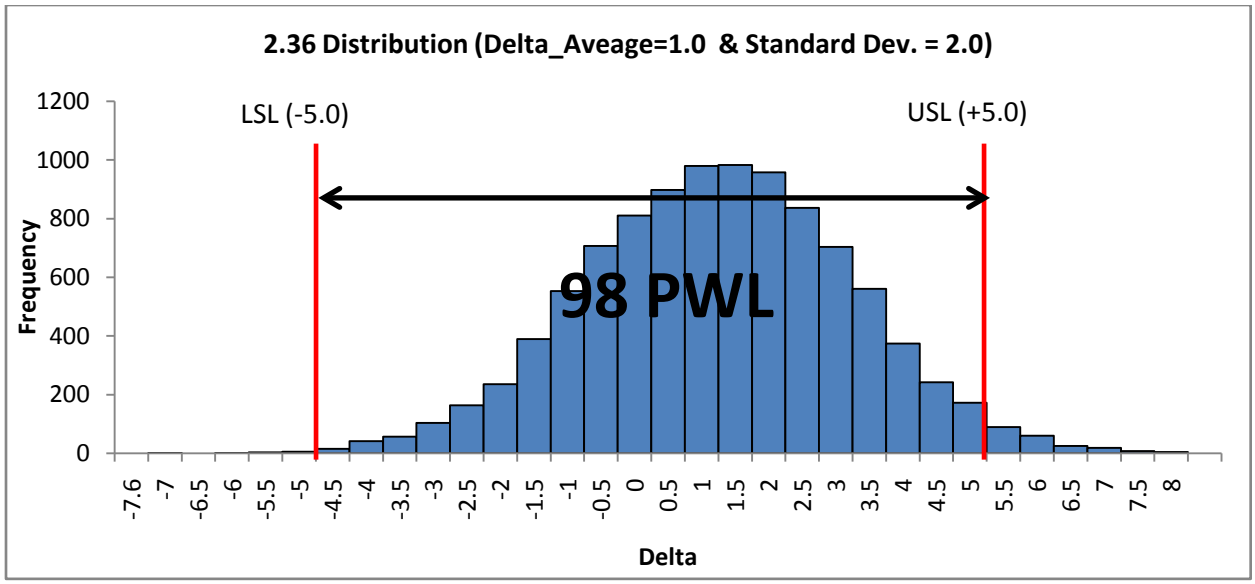

FIGURE 6.21 Distribution of Passing 2.36mm Population and the Tolerances

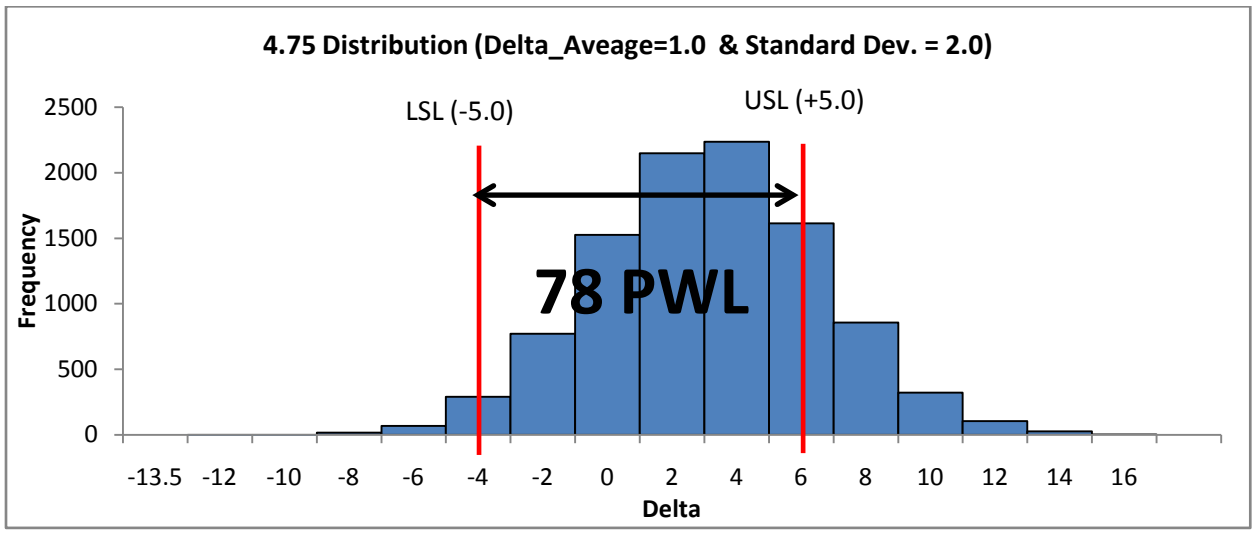

FIGURE 6.22 Distribution of Passing 4.75mm Population and the Tolerances

Figure 6.23 shows the probability of receiving ≥PF (y-axis) in relation to the quality level CMPWL (x-axis), while Table 6.6 summarizes the values obtained at each CMPWL from the simulation analysis.

As it can be seen from table 6.6, when the population standard deviations for the four mixture parameters are used the highest achievable CMPWSL is 92.8. Thus, for values above this level the probability values were interpolated. Furthermore, the simulation analysis have

shown that the probability of receiving a PF< 1 when producing at AQL (90CMPWL) is about 40%, while the probability of receiving a PF≥ 1 when producing at RQL (40CMPWL) is 0%. Similarly the expected pay at any other level of CMPWL, or the probability of receiving different levels of PF at AQL and RQL can be estimated from these results.

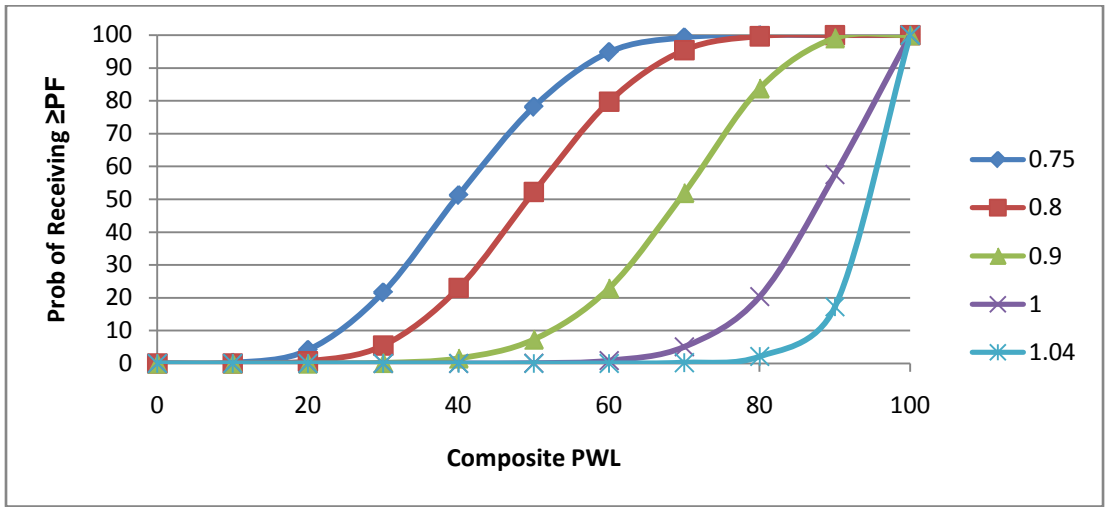

FIGURE 6.23 EP Curves with expected PF Using Population Characteristics (Gap Graded)

TABLE 6.5 Standard Deviation of Different Properties (Gap Graded)

Property	0.075	2.36	4.75	AC
Std. Dev.	0.912	1.969	3.507	0.299

TABLE 6.6 Prob. of Receiving ≥PF at Different CMPWL with Population Characteristics (Gap Graded)

PWL	Prob of Receiving >=PF				
	0.75	**0.8**	**0.9**	**1**	**1.04**
0	0	0	0	0	0
10	0.15	0.01	0	0	0
20	4.06	0.62	0.01	0	0
30	21.66	5.47	0.22	0	0
40	51.25	22.98	1.56	0	0
50	78.08	52.21	7.31	0.13	0
60	94.75	79.73	22.91	0.85	0.01
70	99.31	95.36	51.91	5.05	0.25
80	100	99.63	83.82	20.39	2.17
90	100	99.99	99.04	57.53	17.25
100	100	100	100	100	100

Note1: simulation at 10000 iterations for each CMPWL
Note2: assumed values at 100PWL since only 92.8% of the data fits within spec tolerances

Figures 6.24 and 6.25 show the CMPWL and pay factor distribution. At the long run the average pay factor for a 90.0CMPWL is equal to 1.00, while for RQL the average pay factor is 0.41. Table 6.7 includes the expected pay –EP (PF at the long run) calculations when the population is shifted within the specification tolerances to produce different levels of CMPWL.

TABLE 6.7 Average PF in Relation to CMPWL with Population Characteristics* (Gap Graded)

CMPWL	EP
100.0	1.05
92.9	1.02
90.0	1.00
80.0	0.95
70.0	0.90
60.0	0.81
50.0	0.65
40.0	0.41

Note: * The maximum achievable CMPWL with population standard deviation is 92.9; 100CPWL obtained by reducing population standard deviation by 55%.

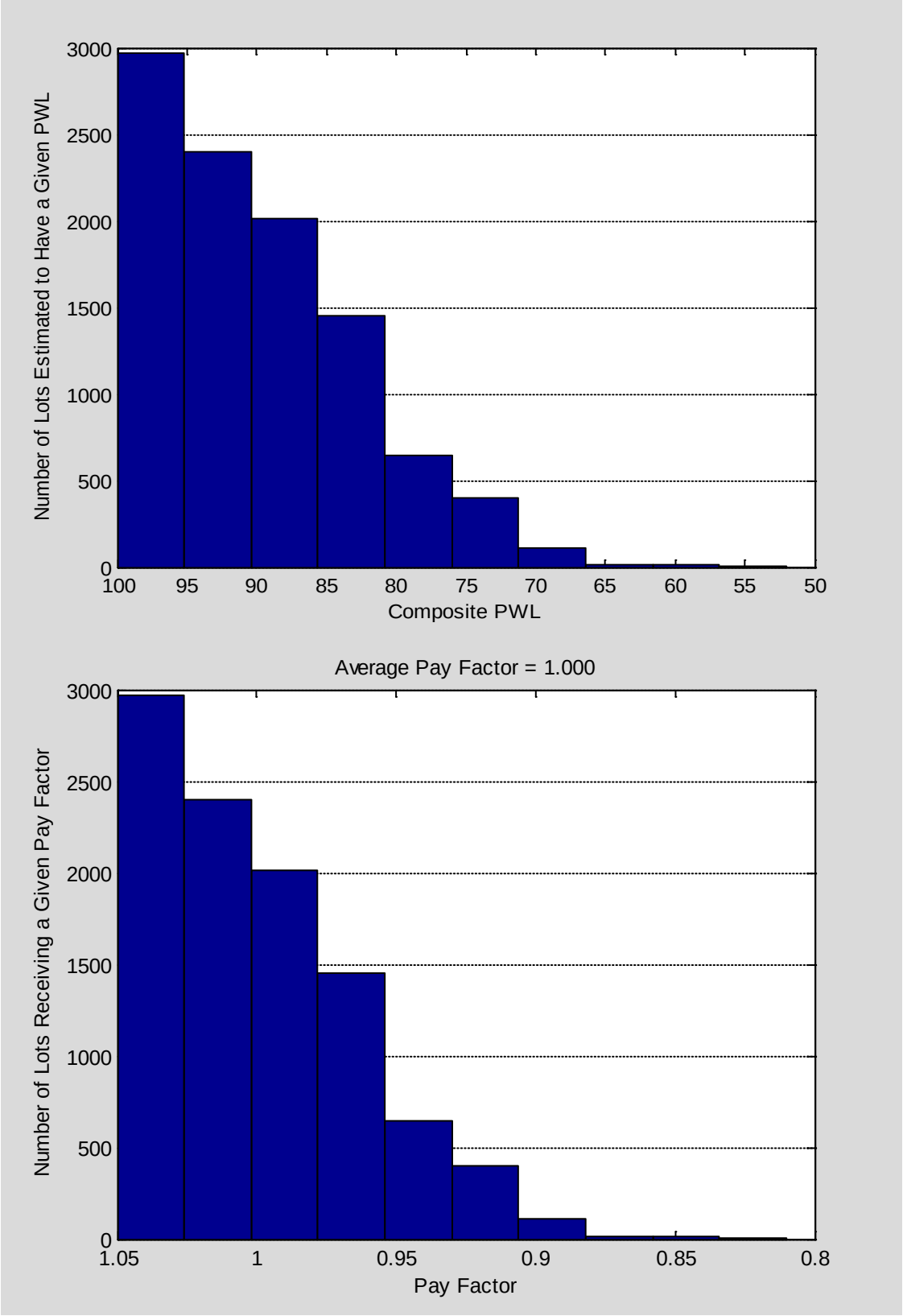

Figure 6.24 Gap Graded CMPWL and Pay Factor Distribution for Production at AQL

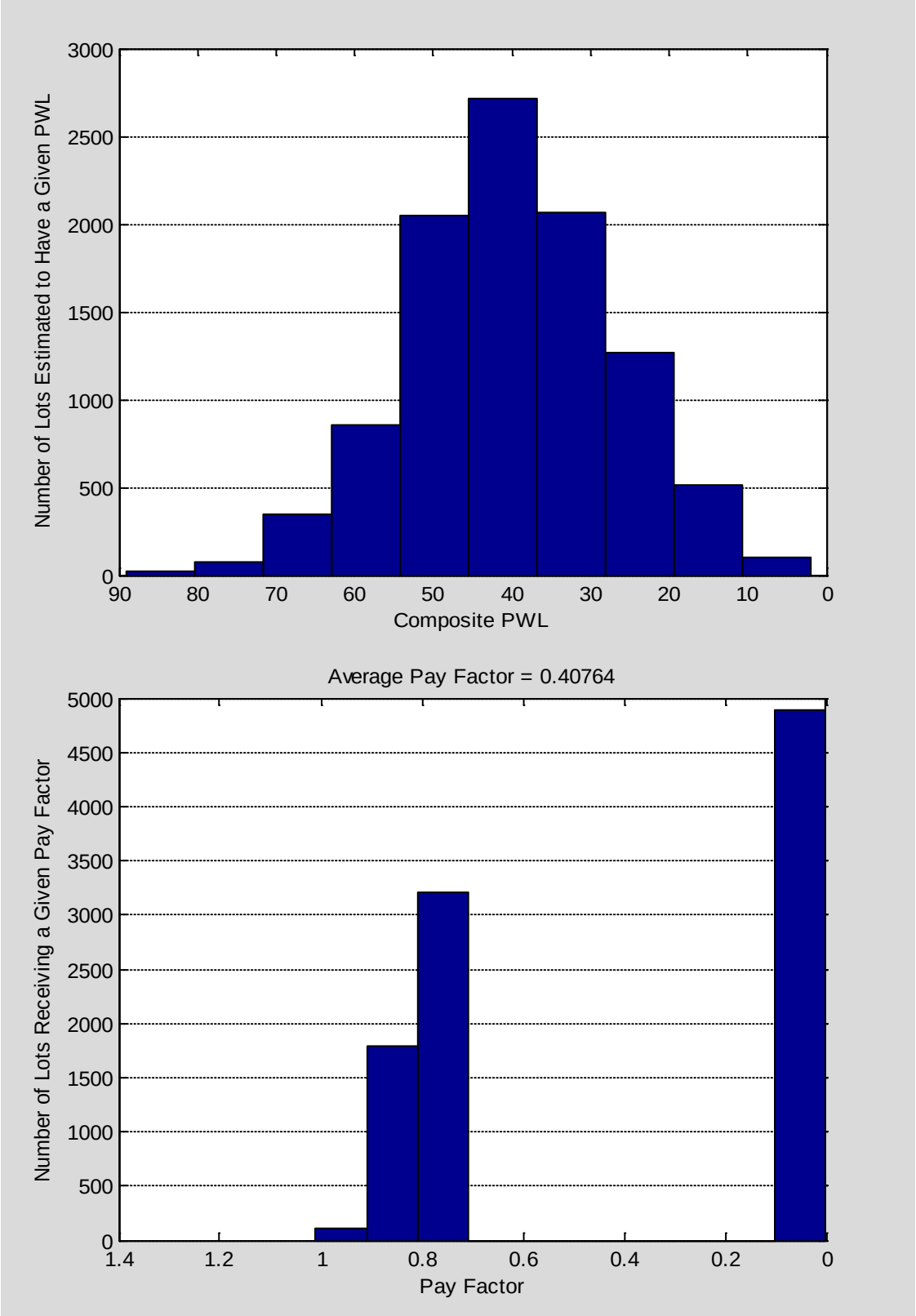

Figure 6.25 Gap Graded CMPWL and Pay Factor Distribution for RQL

6.3 Density Analysis

The density data were divided into two categories: Gap Graded and Dense Graded. This is due to different specifications for each mix type. The original QA and QC data were compared according to the specification with the F & *t* tests on a lot by lot case. The combined QA and QC data provided 1502 recorded data points for gap graded mixes (297 lots) and 4865 for dense graded (972 lots). Out of 297 lots of gap graded mixes, 237 lots passed both tests and the QA and QC values were averaged. For the remaining 60 lots that didn't pass either the F or the *t* test only the QA value was used. Dense graded mixes had 870 lots passing the tests and 102 lots being rejected in at least one of the tests. On average both mixes had 5 sublots per lot. The distributions of all data points and the average of each lot are illustrated below. It should be noted that all the values above 100% and below 85% were considered not acceptable density values and thus were excluded from the analysis. Figures 6.26 to 6.29 show the population distributions for the gap and dense graded mixtures using the sublot (individual values) and the average lot values

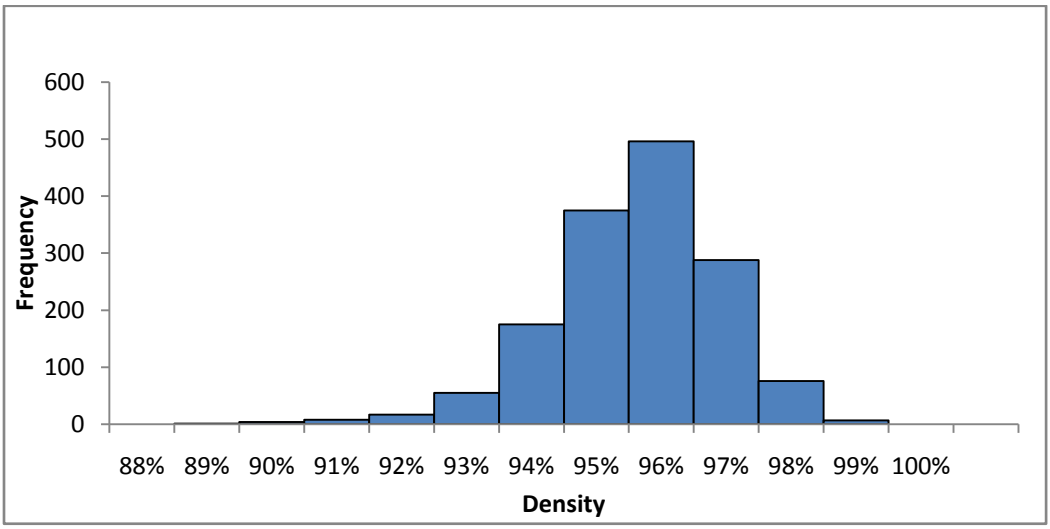

FIGURE 6.26 Distribution of Individual Gap Graded Density Values

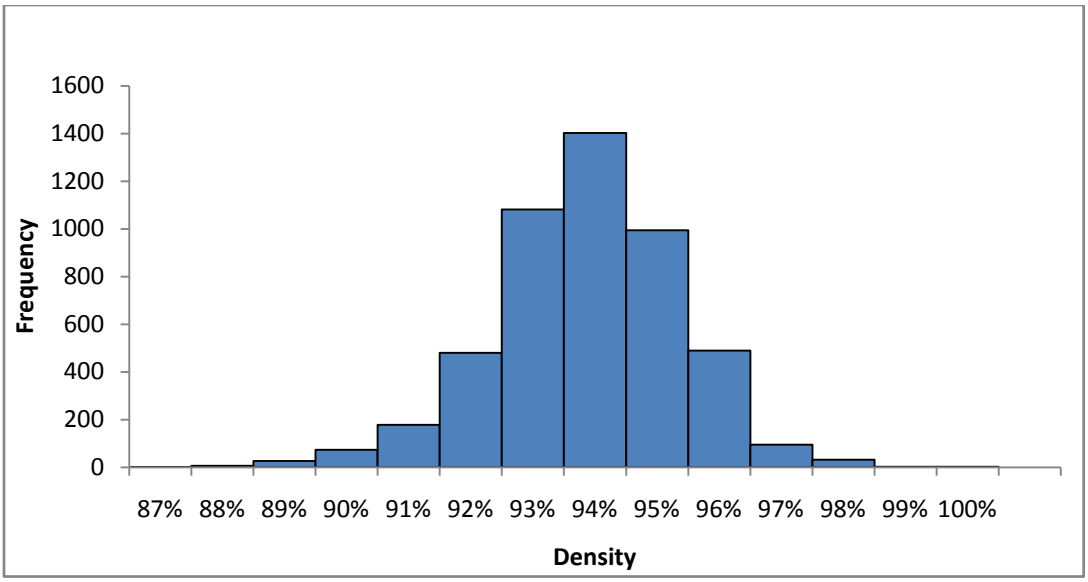

FIGURE 6.27 Distribution of Individual Dense Graded Density Values

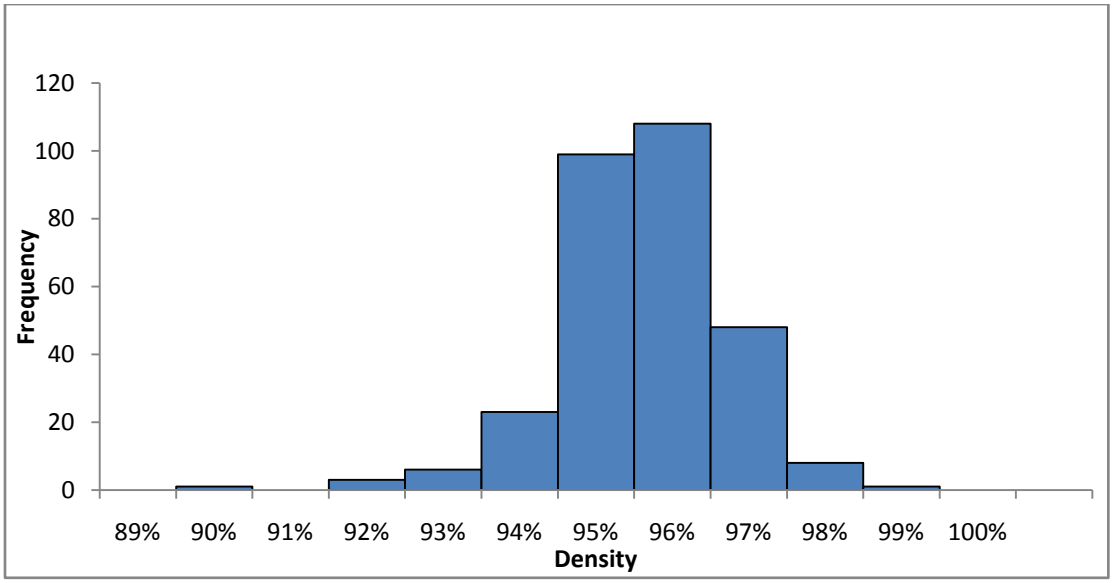

FIGURE 6.28 Distribution of Lot Averages of Gap Graded Density Values

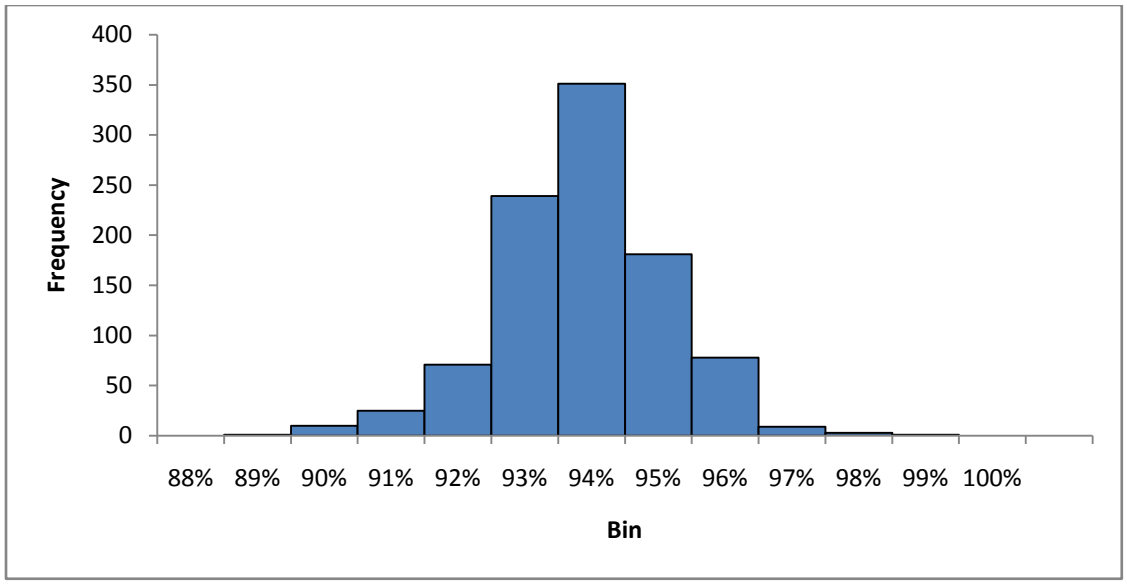

FIGURE 6.29 Distribution of Lot Averages of Dense Graded Density Values

In order to be able to find the best fitting curve for each set of data, different types of distributions were tested by using the built-in functions of MATLAB. Neither of the mixes passed the normality test, therefore the Weibull distribution was used. Each Weibull distribution is defined with two parameters, A and B. A is the scale parameter, so different values stretch or compress the graph in the *x* direction and B is the shape parameter. For both of the mixes these values were calculated and are summarized in Table 6.8.

TABLE 6.8 A and B Parameters for Weibull Distribution of HMA Mixtures

	Individual		**Lot Average**	
Mix	**A**	**B**	**A**	**B**
Gap Graded	95.78	83.43	95.67	98.32
Dense Graded	94.14	64.17	94.04	71.66

Since the pay factor is based on both the sublot and lot average values, the "individual" values were used to in the simulation process where 10000 iterations and 5 samples per iteration were considered. The simulation results are shown in the following Figures, 6.30 to 6.31.

Each of these mixture distributions has a weighted pay factor associated with it. The pay factors are shown in Figures 6.32 and 6.33. As it can be seen at the long run the average pay factor for

density of gap graded is equal to 100% while for dense graded mixtures is 95%. Therefore, the pay schedule provide reasonable PF and doesn't need any modifications, unless the agency wants to promote increased quality in terms of density values, implying adjustments either in the acceptance density values or the pay schedule associated with each density level. An example of such case is included next.

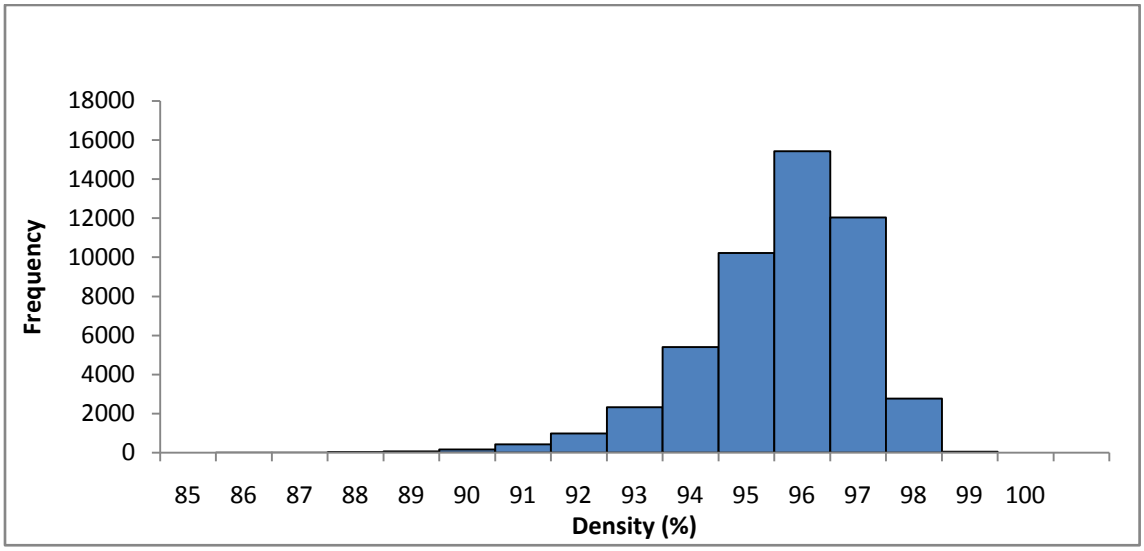

FIGURE 6.30 Distribution of Simulated Density Data of Gap Graded Mixes

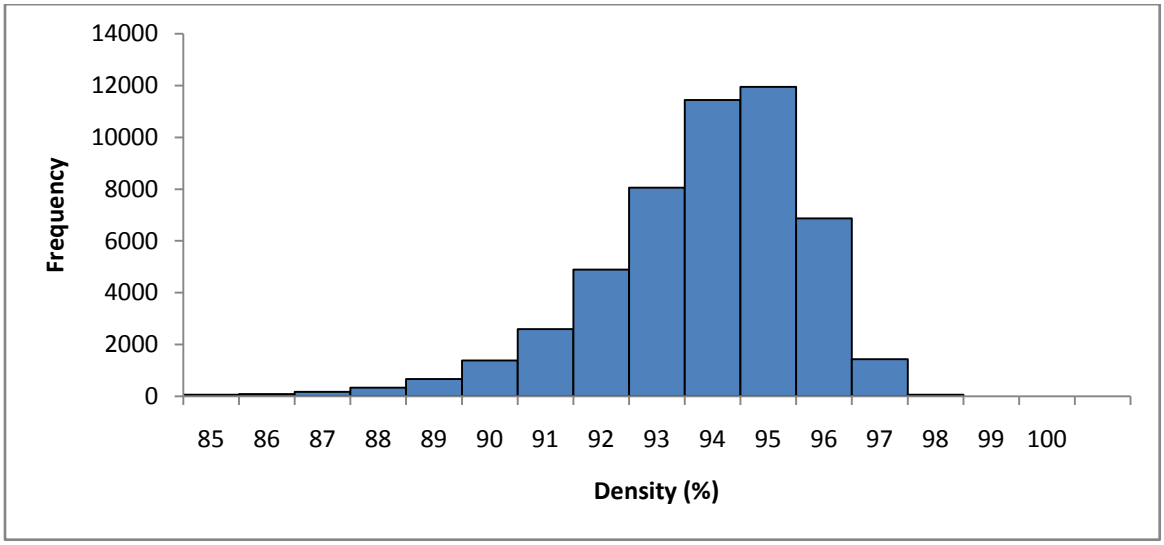

FIGURE 6.31 Distribution of Simulated Density Data of Dense Graded Mixes

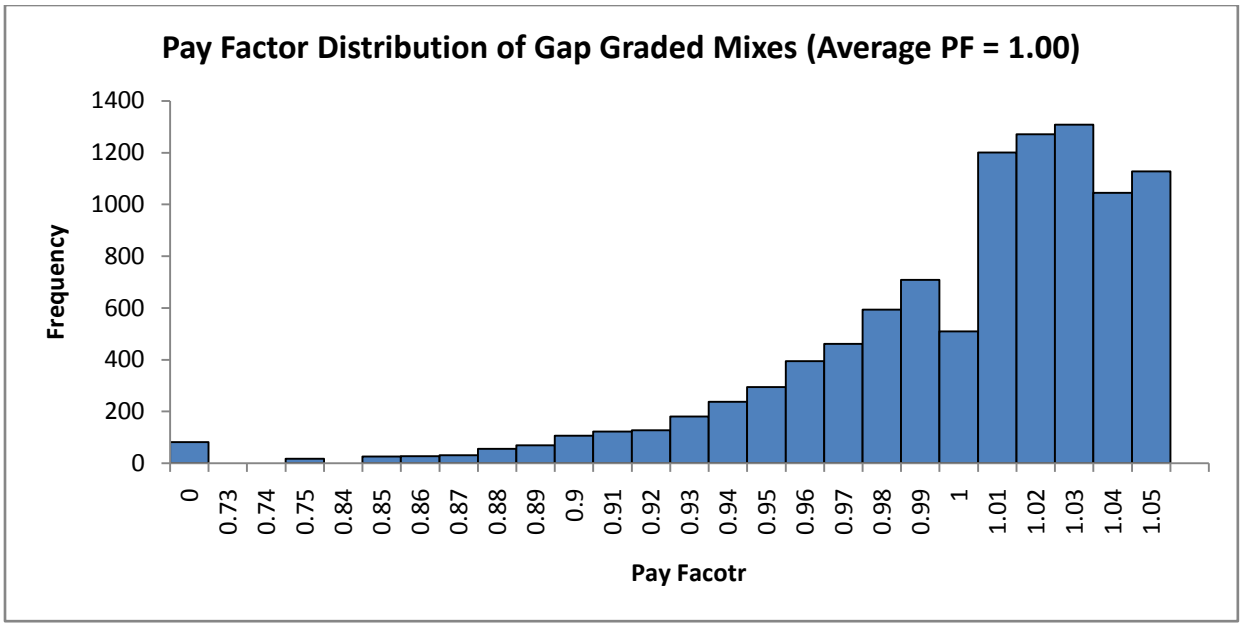

FIGURE 6.32 Pay Factor Distribution of Density Data of Gap Graded Mixes

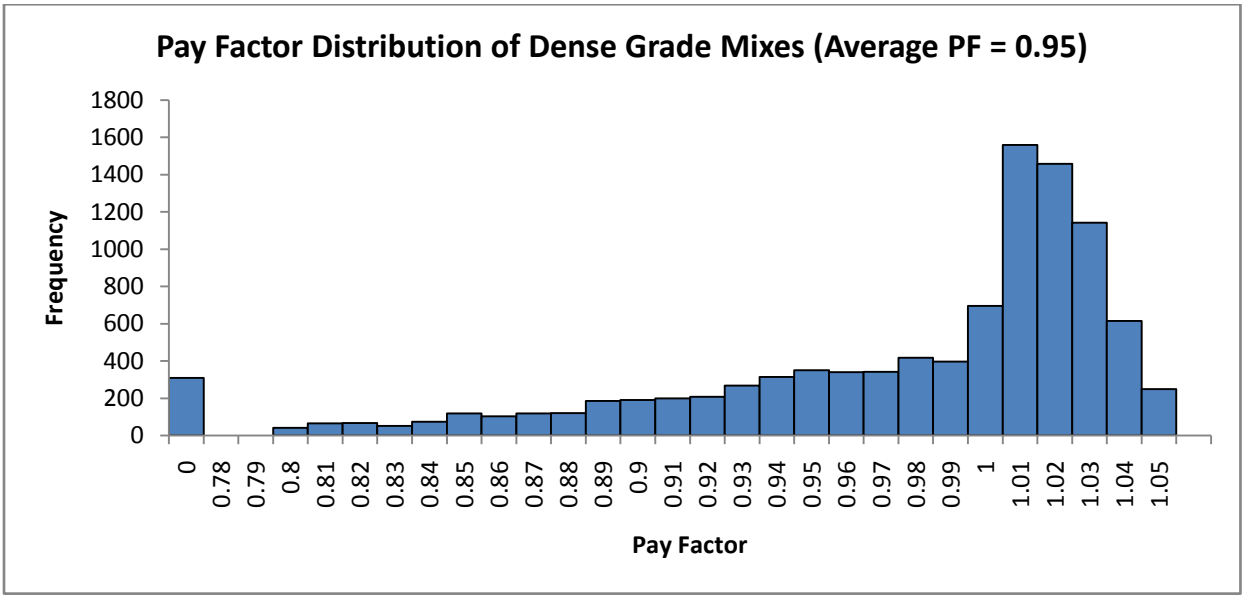

FIGURE 6.33 Pay Factor Distribution of Density of Data of Dense Graded Mixes

Since the average PF for dense graded material is 95%. There are two possible scenarios: 1) The SHA believes that the current quality level deserves 100% PF, on average, or 2) SHA may want the contractors to improve their quality to achieve higher PF. In the first case there is a need to assign a higher PF to the current Lot Average Minimum and Individual minimum. The following table provides an example on the adjustment necessary on the pay schedule in order to

pass from 95% to 100% PF. This pay schedule has up to 12% bonus where the current SHA spec includes a bonus of 5%.

TABLE 6.9 Modified Dense Graded HMA Mixes Percent of Maximum Density

Lot Average % Minimum	No Individual Sublot Below %*	Pay Factor %
94.0	94.0	112.0
93.8	93.7	111.0
93.6	93.4	110.0
93.4	93.1	109.0
93.2	92.8	108.0
93.0	92.5	107.0
92.8	92.2	106.0
92.6	91.9	105.0
92.4	91.6	104.0
92.2	91.3	103.0
92.0	91.0	102.0
91.8	90.8	101.0
91.6	90.6	100.0
91.4	90.4	99.0
91.2	90.2	98.0
91.0	90.0	97.0
90.8	89.8	96.0
90.6	89.6	95.0
90.4	89.4	94.0
90.2	89.2	93.0
90.0	89.0	92.0
89.8	88.8	91.0
89.6	88.6	90.0
89.4	88.4	89.0
89.2	88.2	88.0
89.0	88.0	87.0
88.8	87.8	86.0
88.6	87.6	85.0
88.4	87.4	84.0
88.2	87.2	83.0
88.0	87.0	82.0
Less than 88.0	87.0	75.0 or rejected by Engineer

CHAPTER 7 SUMMARY, CONCLUSIONS & RECOMMENDATIONS

7.1 Summary

Following the implementation of the Superpave mix design method, the Maryland SHA experienced a reduction in asphalt binder content of HMA mixtures that led to durability issues such as premature raveling at joints, increased segregation, and higher permeability.

The review of the past and ongoing NCHRP studies have shown that optimal performance and durability of HMA mixtures can be ensured by: (1) including enough asphalt binder to ensure good fatigue resistance (and, by implication, durability); (2) including adequate mineral filler and fine aggregate to keep permeability low (good for durability) and rut resistance high; and (3) obtaining proper compaction in the field (also good for durability). Since the volumetric variables are interrelated it is difficult to change one volumetric parameter (e.g., design air voids) without simultaneously changing several others (e.g., VBE, VMA, or in-place air voids at a given compaction effort). The four principal recommendations from recent studies for improving the durability of Superpave mixtures while maintaining good rut resistance were: increase effective binder content to provide better fatigue resistance; increase aggregate fineness to decrease mixture permeability; decrease design air voids to ease compaction in the field; and control the in-place air voids effectively. The Maryland SHA introduced a new volumetric mix design specification (Section 904) in 2008 in an effort to improve durability. This new specification reduces N_{design} as an indirect way to increase asphalt content.

In terms of the QA and QC data comparisons, a series of F and *t* tests were performed with data from SHA projects over the past several years. The initial analyses using randomly selecting lots and comparing their means and standard deviations indicated that these two data

sets cannot be considered from the same population. The QA/QC data were further analyzed after disaggregating the data by nominal maximum aggregate size, mix type, and property. Analyses were performed for both paired and unpaired conditions and by matching lots and sublots from each project.

Operating Characteristic curves were then used to identify the alpha and the beta risks for each one of the four mixture characteristic (0.075, 2.36, 4.75, and AC content). The AQL, RQL, and the specification tolerance values were modified to examine their impacts on decision risks. Based on single-variable OC curves, the AQL, RQL and/or tolerances must be modified to achieve the AASHTO recommended alpha and beta values. However, this process was primarily investigative in nature since it does not apply to multi-parameter specifications, and acceptance plans with pay adjustment provisions similar to those at Maryland SHA. For such conditions simulations and expected pay analyses are more appropriate since relate probability of occurrence with expected pay. Thus, a simulation tool was developed to study the effects of reducing asphalt content variability, modifying specification tolerances, and other scenarios on the expected pay factor over the long run. This simulation tool considered the statistical variability of each one of the four HMA mix pay factor parameters as well as their intercorrelations and enables the user to modify all aspects of the specifications and population statistical characteristics. The analyses were performed on both the previous HMA specification without any bonus provisions, and the revised specification which incorporates bonus.

Finally, the simulation analyses were extended to examine the average composite pay factor at AQL and RQL considering all four mixture parameters. Expected pay (EP) curves, were generated for different pay factor levels (0.75, 0.80, 0.90, 1.00 and 1.04).

7.2 Conclusions

From the analysis of this study the following conclusions were obtained:

1. In regards to Maryland State Highway Administration specifications, as it was concluded from previous studies, including a recent NCHRP study, a simple reduction in N_{design} is not necessarily the most effective way of achieving increased mix durability. As mentioned, the true measure of the effectiveness of this new specification will be mixture durability, rutting, and fatigue performance over a period of many years. Thus specific follow up actions are needed to assess the effectiveness of this specification.

2. The F and *t* analyses have shown consistently that the two data sets (QA and QC) eventually represent different populations. The possibility of defining transfer function between mix parameters using the QA and QC data was examined but it proved impossible to develop acceptable relationships.

3. The simulation analyses have shown that, i) while the four mix properties were correlated, the correlations among the mix parameters have no effect on the average pay factor, ii) a contractor with tight control over the variability of mixture production can significantly reduce the AC content and still receive a reasonable pay factor, iii) due to the high weight of the AC content in the final composite pay factor equation, the effects of changing the AC tolerances has a more pronounced impact on the pay factor than any other mixture property, iv) the revised specifications with the bonus provision have provided higher pay factor values than previously. The average PF under the new

specification is very close to 1.00, over the long run, for material meeting or exceeding the AQL.

4. Based on the historical variability of HMA production, the maximum achievable Composite Mix Percent Within Specification Limits (CMPSWL) for dense graded material is 88.7%. The corresponding average mix pay factor (PF) at this quality level is equal to 0.99, over the long run. In order to achieve AQL of 90 CMPSWL with the current population characteristics changes in the specification are needed.

5. The average pay factor at 90 CMPSWL (AQL) is equal to 1.00 for the gap graded mixtures. Thus, the current specification is appropriate for this mixture.

6. Based on the average pay factors the current pay factor equation fairly awards and penalizes the good and bad quality material and there is no need to modify the pay equation. Since the expected pay factor (over the long run) at 40 CMPSWL (RQL) is 0.4 for both dense and gap graded mixtures, the agency bears lower risk for inferior quality material.

7. The simulations and PF analyses for the density data have shown that over the long run the average expected pay factors equal to 1.00 and 0.95 for gap and dense graded mixtures, respectively.

7.3 Recommendations

The following recommendations are suggested from the analyses and conclusions of this study:

1. For evaluating the effectiveness of the Maryland HMA specification the following actions are recommended for determining whether the specification change is having the intended effects, i) comparison of QA binder content data for mixtures designed before and after the specification change to see whether the asphalt percentage has increased as intended, ii) comparison of QA in-place density data for mixtures designed before and after the specification change to see whether lower in-place air voids are now being achieved, iii) review density pay factor schedules to ensure that there is sufficient incentive for contractors to achieve lower in-place air voids.

2. A major difficulty in conducting the QA and QC data analysis was to pair the observations from material in the plant (QC) and behind the paver (QA). Thus a better material identification and tracking techniques is recommended if this study is to be repeated in the future.

3. Even though the revised specification with the bonus provision provided a PF of 1.00, if SHA decides to modify the specification tolerances of the four HMA mix properties to achieve a different average pay factor, it is recommended that the AC tolerance should be addressed first due to its heavy weight in the composite pay factor.

4. Since the EP analysis at AQL have shown that the maximum achievable CMPSWL for dense graded mixtures is 88.7% the specification can be fine tuned to achieve 90 CMPWSL and a PF of 1.00. In order to achieve so, the standard deviation of all four parameters must be reduced by 3.6 percentage points. If the achievable levels of variability in HMA production cannot be improved, then adjustments in the specification tolerances and/or pay factor equation are needed.

5. Since EP at RQL was 0.40 the agency may want to fine tune the specification. As a guide to potential future fine tuning of the specification and pay factor equation, the impact of modifying production variability and/or specification limits has been studied and reported here, along with an alternative method of modifying AQL.

6. For density values whether the agency wants to consider a higher PF at the long run, or improve quality, either adjustments in the acceptance density values or the associated pay schedule may be used. As an example a pay schedule with up to 12% incentive was suggested to increase the current 0.95 PF to 1.00. SHA needs to decide whether this amount of incentive is desired or not, and assess any potential cost/benefit of such large incentive.

As shown in this study the current specifications do provide reasonable rewards and penalties in relation to the HMA production quality. Further monitoring of the specification response and implications of the pay-schedule and bonus provisions is required as HMA production goes on year after year in Maryland.

It is desirable that the implications on pavement performance and agency cost due to superior or inferior HMA quality work be assessed through the development and use of performance based specifications. Under such type of specification the as-built HMA quality is compared to the design- target quality through performance predictions. The costs associated with the differences in performance are then used for evaluating the economic implications. For this purpose performance based specifications should be developed for Maryland. This requires the development of performance prediction models, agency cost models, and eventually user cost models.

Another area that SHA needs to address is issues related to QA/QC data quality, as well as database quality. As it was mentioned, during this study significant effort was needed to pair the QA/QC data and identify potential data entry errors and outliers. Thus, a process is needed to improve such aspects. Eventually the database should be coupled with a verification process of data quality, (perhaps some short of flagging subroutine comparing expected versus input values), before storing the data into the database. The same could be applied to the existing data.

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APPENDIX

A. Simulation Tool

A.1 Description of the Simulation Process

Objective of the simulation tool was to produce a number of normal random lots, calculate the PWL for each parameter (0.075, 2.36, 4.75 and AC) with respect to the spec tolerances and finally provide a histogram of the expected pay and the average pay factor. It should be noted that every aspect of the specs and populations can be modified in this program since all the values are set to be a user input.

The structure of the system in MATLAB is as follows:

1- The number of lots, number of sublots, target value of production, standard deviation of all four properties and the tolerances are given as inputs.

2- Random normal lots are generated based on the correlation matrix of the four properties. The method used to generate “Random Normal Correlated” numbers is the Cholesky decomposition. The correlation matrix was found using all the previous data recorded in the data base, Table A1.

3- The produced lots are then processed in accordance with MSMT 735 to obtain the CMPWSL of each lot.

4- The CMPWSL is then translated to the Mix Pay Factor of that lot based on section 504.04.02 of State Highway Administration Special Provision Insert Category 500.

5- The histograms of the Mix Pay Factors are generated by MATLAB which were the ultimate tool for our final conclusions.

The flow chart below summarizes the preceding steps:

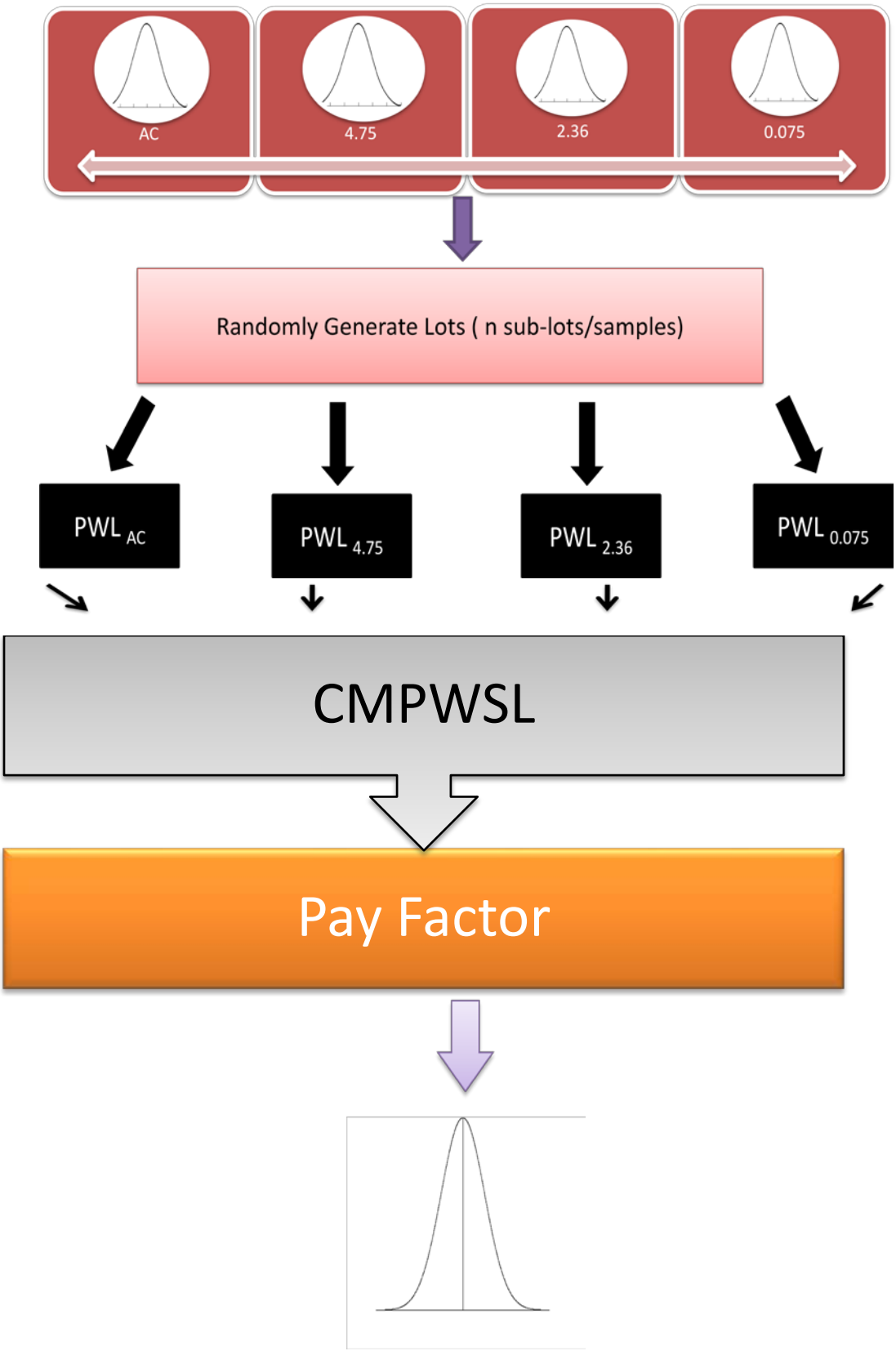

FIGURE A1 Flow Chart of Simulation Analysis

A.2 MATLAB Codes of the Simulation Tool for HMA Mix Properties

```
%SSK
close all
clear
clc
PL_PU_Matrix;
h=input('delta Value=');
u=input('sd value=');
m=10000;
n=6;
if n<3 | n>300
   fprintf('Number of Sublots Must be 3<n<300 \n')
   n=input('Please Enter a Value (3<n<300) for the Number of Sublots=');
   if n<3 | n>300
   button = questdlg('n must be 3<n<300 do you understand?', ...
                     'Exit Dialog','Yes','No','No');
       switch button
         case 'Yes',
           n=input('Please Enter a Value (3<n<300) for the Number of Sublots=');
           if n<3 | n>300
           disp('Exiting MATLAB');
           exit
           end
         case 'No',
           exit;
       end
   end
end
% delta_ZERO=input('Mean of plant production minus target value for 0.075=');
% delta_TWO=input('Mean of plant production minus target value for 2.36=');
% delta_FOUR=input('Mean of plant production minus target value for 4.75=');
% delta_AC=input('Mean of plant production minus target value for AC=');
% delta=[delta_ZERO,delta_TWO,delta_FOUR,delta_AC];
%  delta=[0.992,-.192,0.066,-0.002];
delta=[-2+(2*h),-5+(5*h),-5+(5*h),-0.5+(.5*h)];
% std_dev_ZERO=input('std_dev for 0.075=');
% std_dev_TWO=input('std_dev for 2.36=');
% std_dev_FOUR=input('std_dev for 4.75=');
% std_dev_AC=input('std_dev for AC=');
% sd = [std_dev_ZERO,std_dev_TWO,std_dev_FOUR,std_dev_AC];
sd = [0.912-(0.912*u),1.969-(1.969*u),3.507-(3.507*u),0.299-(0.299*u)];
SL=[2,5,5,0.5];
f_ZERO_TWO_FOUR_AC=[24,7,7,62];
CORR
=[1.0000,0.3377,0.2085,0.2423;0.3377,1.0000,0.5620,0.2607;0.2085,0.5620,1.0000,0.3048;0.2423,0.2607,0.3048,1.
0000];
% CORR =[1.0000,h,h,h;h,1.0000,h,h;h,h,1.0000,h;h,h,h,1.0000];
USL=SL;
LSL=-SL;
for k=1:m
  T = CORR;
   for u=1:1:4
      T(:,u) = T(:,u) * sd(u);
   end
```

```
    for r=1:1:4
        T(r,:) = T(r,:) * sd(r);
    end
    % now T is the covariance matrix
    B = chol(T);
    N_ZERO = normrnd(0,1,n,1);
    N_TWO = normrnd(0,1,n,1);
    N_FOUR = normrnd(0,1,n,1);
    N_AC = normrnd(0,1,n,1);
    N=[N_ZERO,N_TWO,N_FOUR,N_AC];
    X = N*B;
    X=X+repmat(delta,n,1);
%     B = chol(T);
%     N_ZERO = normrnd(0,3.57,n,1);
%     N_TWO = normrnd(0,8.93,n,1);
%     N_FOUR = normrnd(0,12.50,n,1);
%     N_AC = normrnd(0,.89,n,1);
%     N=[N_ZERO,N_TWO,N_FOUR,N_AC];
%     X = N;
    %MSMT 735
    MEAN=mean(X);
    STDEV=std(X);
    QU=chop((USL-MEAN)./STDEV,3);
    QL=chop((MEAN-LSL)./STDEV,3);
    p=n-1;
    for j=1:4;
        for i=1:50;
            if (QU(1,j)==A(i,p))
                PU(1,j)=A(i,1);
            end
            if (QU(1,j)>A(i+1,p) & QU(1,j)<A(i,p))
                PU(1,j)=A(i,1);
            end
            if (QU(1,j)>A(1,p))
                PU(1,j)=100;
            end
            if (-QU(1,j)==A(i,p))
                 PU(1,j)=100-A(i,1);
            end
            if (-QU(1,j)>A(i+1,p) & -QU(1,j)<A(i,p))
                 PU(1,j)=100-A(i,1);
            end
            if (-QU(1,j)>A(1,p))
                 PU(1,j)=0;
            end
            if (QL(1,j)==A(i,p))
                PL(1,j)=A(i,1);
            end
            if (QL(1,j)>A(i+1,p) & QL(1,j)<A(i,p))
                PL(1,j)=A(i,1);
            end
            if (QL(1,j)>A(1,p))
                PL(1,j)=100;
            end
            if (-QL(1,j)==A(i,p))
                 PL(1,j)=100-A(i,1);
```

```
        end
        if (-QL(1,j)>A(i+1,p) & -QL(1,j)<A(i,p))
            PL(1,j)=100-A(i,1);
        end
        if (-QL(1,j)>A(1,p))
            PL(1,j)=0;
        end
      end
      PWSL(1,j)=PU(1,j)+PL(1,j)-100;
   end
CMPWSL(1,k)=round([sum(PWSL.*f_ZERO_TWO_FOUR_AC)/sum(f_ZERO_TWO_FOUR_AC)]);
if (CMPWSL(1,k)<40)
   MF(1,k)=0;
end
% if (CMPWSL(1,k)<90 & CMPWSL(1,k)>=40)
%     MF(1,k)=0.55+0.5*CMPWSL(1,k)/100;
% end
% if (CMPWSL(1,k)>=90)
%     MF(1,k)=1;
% end
if (CMPWSL(1,k)<=100 & CMPWSL(1,k)>=40)
   MF(1,k)=0.55+0.5*CMPWSL(1,k)/100;
end
end
hist(CMPWSL);
% grid;
xlabel('Composite PWL');
ylabel('Number of Lots Estimated to Have a Given PWL');
Mean_CMPWSL=mean(CMPWSL);
Std_CMPWSL=std(CMPWSL);
Mean_MF=mean(MF);
Std_MF=std(MF);
Meadian_MF=median(MF);
figure;
hist(MF);
% grid;
PF75=sum(histc(MF,.75:.01:1.05))/m*100;
PF80=sum(histc(MF,.80:.01:1.05))/m*100;
PF90=sum(histc(MF,.90:.01:1.05))/m*100;
PF100=sum(histc(MF,1.00:.01:1.05))/m*100;
PF104=sum(histc(MF,1.04:.01:1.05))/m*100;
PF=[PF75,PF80,PF90,PF100,PF104]
RISK=[(100-PF100)/100,PF100];
% Histogram_CountCM=histc(CMPWSL,90:2.5:100);
% xlabel('Mixture Pay Factor');
% ylabel('Frequency');
format short g;
Delta_MF=MF-Mean_MF;
Mean_Delta_MF=mean(Delta_MF);
Total_Delta_MF=sum(Delta_MF);
Report=[m n delta sd Mean_CMPWSL Std_CMPWSL Mean_MF Std_MF];
Report=[Mean_CMPWSL,Mean_MF]
% sum(Histogram_Count)
```

A.3 MATLAB Codes of the Simulation Tool for the Density Analysis

A.3.1 Gap Graded

```
%SSK
close all
clear
clc
m=input('Number of Lots=');
n=input('Number of Sublots=');
G=xlsread('C:\Documents and Settings\Sahand\Desktop\MSHA
project\Density_Final.xls','Gap_Graded_Ind','a2:a1503')*100;
GW=wblfit(G);
for k=1:m
XG=wblrnd(GW(1),GW(2),n,1);
MEAN=mean(XG);
MIN=min(XG);
for i=1:n
   if XG(i)<85
      XG(i)=85;
   end
   if XG(i)>100
      XG(i)=100
   end
end
N(k*n:(k*n+n-1),1)=XG;
      if (MEAN<91.0)
         PF(1,k)=0.75;
      end
      if (MEAN>=91.0 & MIN>=88.5)
         PF(1,k)=0.85;
      end
      if (MEAN>=91.2 & MIN>=88.8)
         PF(1,k)=0.86;
      end
      if (MEAN>=91.4 & MIN>=89.1)
         PF(1,k)=0.87;
      end
      if (MEAN>=91.6 & MIN>=89.4)
         PF(1,k)=0.88;
      end
      if (MEAN>=91.8 & MIN>=89.7)
         PF(1,k)=0.89;
      end
      if (MEAN>=92.0 & MIN>=90.0)
         PF(1,k)=0.90;
      end
      if (MEAN>=92.2 & MIN>=90.3)
         PF(1,k)=0.91;
      end
      if (MEAN>=92.4 & MIN>=90.6)
         PF(1,k)=0.92;
      end
      if (MEAN>=92.6 & MIN>=90.9)
         PF(1,k)=0.93;
```

```
end
if (MEAN>=92.8 & MIN>=91.2)
   PF(1,k)=0.94;
end
if (MEAN>=93.0 & MIN>=91.5)
   PF(1,k)=0.95;
end
if (MEAN>=93.2 & MIN>=91.8)
   PF(1,k)=0.96;
end
if (MEAN>=93.4 & MIN>=92.1)
   PF(1,k)=0.97;
end
if (MEAN>=93.6 & MIN>=92.4)
   PF(1,k)=0.98;
end
if (MEAN>=93.8 & MIN>=92.7)
   PF(1,k)=0.99;
end
if (MEAN>=94.0 & MIN>=93.0)
   PF(1,k)=1.00;
end
if (MEAN>=94.1 & MIN>=93.2)
   PF(1,k)=1.005;
end
if (MEAN>=94.2 & MIN>=93.4)
   PF(1,k)=1.01;
end
if (MEAN>=94.3 & MIN>=93.6)
   PF(1,k)=1.015;
end
if (MEAN>=94.4 & MIN>=93.8)
   PF(1,k)=1.02;
end
if (MEAN>=94.5 & MIN>=94)
   PF(1,k)=1.025;
end
if (MEAN>=94.6 & MIN>=94.2)
   PF(1,k)=1.03;
end
if (MEAN>=94.7 & MIN>=94.4)
   PF(1,k)=1.035;
end
if (MEAN>=94.8 & MIN>=94.6)
   PF(1,k)=1.04;
end
if (MEAN>=94.9 & MIN>=94.8)
   PF(1,k)=1.045;
end
if (MEAN>=95 & MIN>=95)
   PF(1,k)=1.05;
end
if (MEAN>97.5)
   PF(1,k)=0.75;
end
if sum(sum(XG>97))==3
```

```
        PF(1,k)=0.75;
        end
        if sum(sum(XG>97.5))>=4
          PF(1,k)=0.75;
        end
end
PF;
mean(PF)
for i=1:m
   PFF(i,1)=PF(1,i);
end
% xlswrite('c:\density.xls',PFF)
```

A.3.2 Dense Graded

```
%SSK
close all
clear
clc
m=input('Number of Lots=');
n=input('Number of Sublots=');
D=xlsread('C:\Documents and Settings\Sahand\Desktop\MSHA
project\Density_Final.xls','Dense_Graded_Ind','a2:a4866')*100;
DW=wblfit(D)
for k=1:m
XD=wblrnd(DW(1),DW(2),n,1);
MEAN=mean(XD);
MIN=min(XD);
for i=1:n
   if XD(i)<85
      XD(i)=85;
   end
   if XD(i)>100
      XD(i)=100
   end
end
N(k*n:(k*n+n-1),1)=XD;
        if (XD(i)<87.0)
           PF(1,k)=0;
        end
        if (MEAN<88.0 & MIN>=87.0)
           PF(1,k)=0.75;
        end
        if (MEAN>=88.0 & MIN>=87.0)
           PF(1,k)=0.80;
        end
        if (MEAN>=88.2 & MIN>=87.2)
           PF(1,k)=0.81;
        end
        if (MEAN>=88.4 & MIN>=87.4)
           PF(1,k)=0.82;
        end
        if (MEAN>=88.6 & MIN>=87.6)
           PF(1,k)=0.83;
```

```
end
if (MEAN>=88.8 & MIN>=87.8)
   PF(1,k)=0.84;
end
if (MEAN>=89.0 & MIN>=88.0)
   PF(1,k)=0.85;
end
if (MEAN>=89.2 & MIN>=88.2)
   PF(1,k)=0.86;
end
if (MEAN>=89.4 & MIN>=88.4)
   PF(1,k)=0.87;
end
if (MEAN>=89.6 & MIN>=88.6)
   PF(1,k)=0.88;
end
if (MEAN>=89.8 & MIN>=88.8)
   PF(1,k)=0.89;
end
if (MEAN>=90.0 & MIN>=89.0)
   PF(1,k)=0.90;
end
if (MEAN>=90.2 & MIN>=89.2)
   PF(1,k)=0.91;
end
if (MEAN>=90.4 & MIN>=89.4)
   PF(1,k)=0.92;
end
if (MEAN>=90.6 & MIN>=89.6)
   PF(1,k)=0.93;
end
if (MEAN>=90.8 & MIN>=89.8)
   PF(1,k)=0.94;
end
if (MEAN>=91.0 & MIN>=90.0)
   PF(1,k)=0.95;
end
if (MEAN>=91.2 & MIN>=90.2)
   PF(1,k)=0.96;
end
if (MEAN>=91.4 & MIN>=90.4)
   PF(1,k)=0.97;
end
if (MEAN>=91.6 & MIN>=90.6)
   PF(1,k)=0.98;
end
if (MEAN>=91.8 & MIN>=90.8)
   PF(1,k)=0.99;
end
if (MEAN>=92 & MIN>=91)
   PF(1,k)=1.00;
end
if (MEAN>=92.2 & MIN>=91.3)
   PF(1,k)=1.005;
end
if (MEAN>=92.4 & MIN>=91.6)
```

```
        PF(1,k)=1.01;
      end
      if (MEAN>=92.6 & MIN>=91.9)
        PF(1,k)=1.015;
      end
      if (MEAN>=92.8 & MIN>=92.2)
        PF(1,k)=1.02;
      end
      if (MEAN>=93 & MIN>=92.5)
        PF(1,k)=1.025;
      end
      if (MEAN>=93.2 & MIN>=92.8)
        PF(1,k)=1.03;
      end
      if (MEAN>=93.4 & MIN>=93.1)
        PF(1,k)=1.035;
      end
      if (MEAN>=93.6 & MIN>=93.4)
        PF(1,k)=1.04;
      end
      if (MEAN>=93.8 & MIN>=93.7)
        PF(1,k)=1.045;
      end
      if (MEAN>=94 & MIN>=94)
        PF(1,k)=1.05;
      end
      if (MEAN>97.5)
        PF(1,k)=0.75;
      end
      if sum(sum(XD>97))==3
      PF(1,k)=0.75;
      end
      if sum(sum(XD>97.5))>=4
       PF(1,k)=0.75;
      end
end
PF;
mean(PF)
for i=1:m
   PFF(i,1)=PF(1,i);
end
xlswrite('c:\density.xls',PFF)
```

A.4 Implications of Correlation Coefficients on PF

Based on the correlation coefficients for dense graded mixtures, several analyses show that their effects had no impact on the pay factor analysis. In the example of Table A1 the values of the correlations were changed ranging from 0.001 to 0.999. As it can be seen no effects on PF were observed. The correlations of four mix parameters for gap graded mixtures were not established since limited data were available for these mixtures

TABLE A1 Example of Effect of Correlation Value on the Average PF

Average CMPWL	Std. Dev. CMPWL	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

B. Impact of Reducing Population Variability and/or Modifying Spec Tolerances

TABLE B1 Effects of Reducing Population Standard Deviation

	at AQL (90CMPWL)		at RQL (40 CMPWL)	
% Reduction in SD_{pop}	Probability of receiving a PF< 1	Average PF	Probability of receiving a PF≥ 1	Average PF
0.0%	N/A	N/A	0.01	0.41
3.6%	0.40	1.00	0.00	0.41
5.0%	0.40	1.00	0.00	0.41
10.0%	0.40	1.00	0.00	0.41
20.0%	0.39	1.00	0.00	0.41
35.0%	0.41	1.00	0.01	0.41
50.0%	0.40	1.00	0.00	0.41

TABLE B2 Effects of Increasing Spec Tolerances

	at AQL (90CMPWL)		at RQL (40 CMPWL)	
% Increase in Tolerance	Probability of receiving a PF< 1	Average PF	Probability of receiving a PF≥ 1	Average PF
0.0%	N/A	N/A	0.01	0.41
3.6%	0.40	1.00	0.00	0.41
5.0%	0.40	1.00	0.00	0.41
10.0%	0.40	1.00	0.00	0.41
20.0%	0.40	1.00	0.00	0.41
35.0%	0.40	1.00	0.00	0.41
50.0%	0.41	1.00	0.01	0.41

C. Alternative Approach for Defining HMA Specifications

This section identifies an alternative approach for modifying mix property PF parameters at AQL and RQL. This method is based on the procedure adopted by WSDOT (Mahoney, and Muench, 2001) and requires the definition of PF in function of PWL and sample size, similar to the ones reported in Table B1. To be noticed that the WSDOT procedure, does not address correlated quality characteristics. This increases the risk to the contractor because if he/she is penalized on one sieve, the probability certainly increases that he will be penalized on the other. There has been some debate over the use of the acceptance "c" factor used by WSDOT and FHWA Western Federal Lands. There are two schools of thought; 1) the adjustment using the "c' factor is necessary to address small sample sizes; and 2) that the PWL analysis already incorporates sample size in the estimate of the PWL, so the "c" factor overcompensates. In fact, whether it is stated or not an acceptance value of 73CMPWL by definition actually sets the AQL at 73 PWL.

This approach is based on the definition of an acceptance value, c, which is the lot quality associated with a pay factor of 1.00. The steps for quantifying this parameter include:

1. Determine the acceptable quality limit (AQL) in percent defective (PD).

$$PD = 100 - PWL$$

2. Set the primary α risk (the contractor's risk that material produced at AQL will be either rejected or subject to reduced pay).
3. Determine the sample size to be used (n).

4. Determine the z-statistic associated with the primary α risk, z(αc). This is just the cumulative normal probability value associated with the primary α risk and can be obtained with Microsoft Excel (NORMSDIST function) or standard statistical tables.

5. Use the basic equation below to solve for z_c.

$$z(\alpha_c) = \sqrt{n}\,(z_{AQL} - z_c)$$

where: $z(\alpha_c)$ = z-statistic associated with the primary α risk

z_{AQL} = z-statistic associated with AQL

z_c = z-statistic associated with the acceptance value (c)

n = sample size

6. Determine the acceptance value (c) from z_c . This can be done with Microsoft Excel (NORMSINV function) or standard statistical tables.

TABLE C1 WSDOT Pay Factors

Pay Factors

Required Quality Level for a Given Sample Size (n) and a Given Pay Factor

Pay Factor (PF)	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10 to n=11	n=12 to n=14	n=15 to n=18	n=19 to n=25	n=26 to n=37	n=38 to n=69	n=70 to n=200	n=201 to n=∞
1.05	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
1.04	90	91	92	93	93	93	94	94	95	95	96	96	97	97	99
1.03	80	85	87	88	89	90	91	91	92	93	93	94	95	96	97
1.02	75	80	83	85	86	87	88	88	89	90	91	92	93	94	95
1.01	71	77	80	82	84	85	85	86	87	88	89	90	91	93	94
1.00	68	74	78	80	81	82	83	84	85	86	87	89	90	91	93
0.99	66	72	75	77	79	80	81	82	83	85	86	87	88	90	92
0.98	64	70	73	75	77	78	79	80	81	83	84	85	87	88	90
0.97	62	68	71	74	75	77	78	78	80	81	83	84	85	87	89
0.96	60	66	69	72	73	75	76	77	78	80	81	83	84	86	88
0.95	59	64	68	70	72	73	74	75	77	78	80	81	83	85	87
0.94	57	63	66	68	70	72	73	74	75	77	78	80	81	83	86
0.93	56	61	65	67	69	70	71	72	74	75	77	78	80	82	84
0.92	55	60	63	65	67	69	70	71	72	74	75	77	79	81	83
0.91	53	58	62	64	66	67	68	69	71	73	74	76	78	80	82
0.90	52	57	60	63	64	66	67	68	70	71	73	75	76	79	81
0.89	51	55	59	61	63	64	66	67	68	70	72	73	75	77	80
0.88	50	54	57	60	62	63	64	65	67	69	70	72	74	76	79
0.87	48	53	56	58	60	62	63	64	66	67	69	71	73	75	78
0.86	47	51	55	57	59	60	62	63	64	66	68	70	72	74	77
0.85	46	50	53	56	58	59	60	61	63	65	67	69	71	73	76
0.84	45	49	52	55	56	58	59	60	62	64	65	67	69	72	75
0.83	44	48	51	53	55	57	58	59	61	63	64	66	68	71	74
0.82	42	46	50	52	54	55	57	58	60	61	63	65	67	70	72
0.81	41	45	48	51	53	54	56	57	58	60	62	64	66	69	71
0.80	40	44	47	50	52	53	54	55	57	59	61	63	65	67	70
0.79	38	43	46	48	50	52	53	54	56	58	60	62	64	66	69
0.78	37	41	45	47	49	51	52	53	55	57	59	61	63	65	68
0.77	36	40	43	46	48	50	51	52	54	56	57	60	62	64	67
0.76	34	39	42	45	47	48	50	51	53	55	56	58	61	63	66
0.75	33	38	41	44	46	47	49	50	51	53	55	57	59	62	65

Reject Quality Levels Less Than Those Specified for a 0.75 Pay Factor

Note: If the computed Quality Level does not correspond exactly to a figure in the table, use the next lower value.

Example analysis: Using Population Characteristics

Based on this procedure example analysis were carried out using the population characteristics for two levels of α risk, 5% and 1%. The c values obtained with the above procedure provided CMPWL of 73% and 63%, respectively for a sample size of 6, reflecting the SHA practice. The OC Curves were then generated. The results for an α risk of 5% are shown in Table B2 and Figure B1. The α (equal to 1-97.88) and □ (equal to 0.84) risks are calculated based on the values highlighted in Table B2.

Similarly the results for an α risk of 1% are reported in Table B3 and Figure B2.

TABLE C2 Probability of Receiving ≥PF at Different CMPWL Using Population Characteristics & C = 73CMPWL (α=5%)

PWL	Prob of Receiving >=PF			
	0.75	**0.8**	**0.9**	**1**
0	0	0	0	0
10	0.14	0.04	0	0
20	4.20	0.48	0.03	0.02
30	22.37	5.77	0.20	0.14
40	51.18	22.59	1.43	0.84
50	78.58	50.91	6.69	4.32
60	94.47	80.79	23.95	17.47
70	99.26	95.66	53.21	43.96
80	99.97	99.69	84.14	76.67
88.95	100	100	99.17	97.88
100	100	100	100	100

Note1: 10000 iterations at each PWL
Note2: The values at 100PWL are interpolated

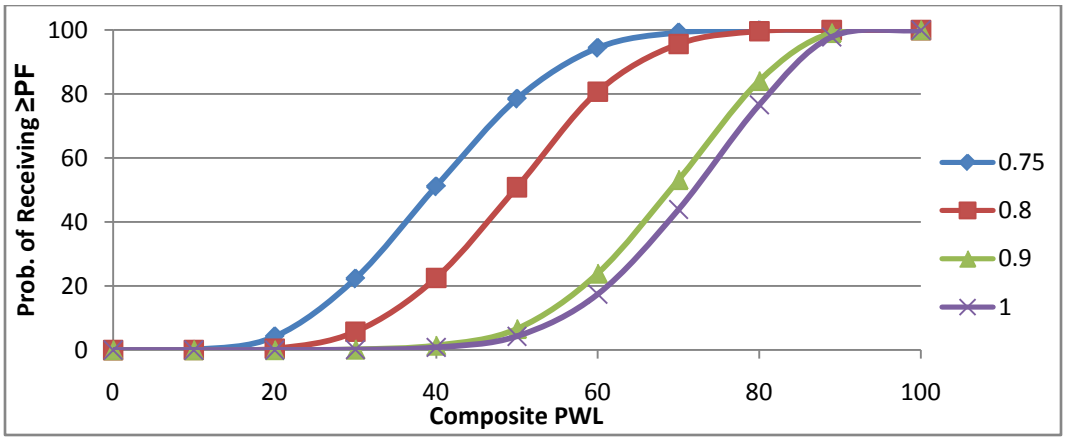

FIGURE C1 EP Curves with Expected PF Using Population Standard Deviation and C = 73 CMPWL (α=5%)

TABLE C3 Probability of Receiving ≥PF at Different CMPWL Using Population Characteristics and C = 63CMPWL (α=1%)

CMPWL	Prob of Receiving >=PF			
	0.75	0.8	0.9	1
0	0	0	0	0
10	0.09	0.01	0	0
20	4.33	0.68	0.02	0.02
30	21.45	5.87	0.66	0.66
40	50.64	22.18	4.12	4.12
50	79.08	51.68	17.03	17.03
60	94.38	80.51	43.13	43.13
70	99.29	95.52	74.82	74.82
80	99.96	99.7	95.38	95.38
88.781	100	100	99.91	99.91
100	100	100	100	100

Note1: 10000 iterations at each PWL
Note2: The values at 100PWL are interpolated

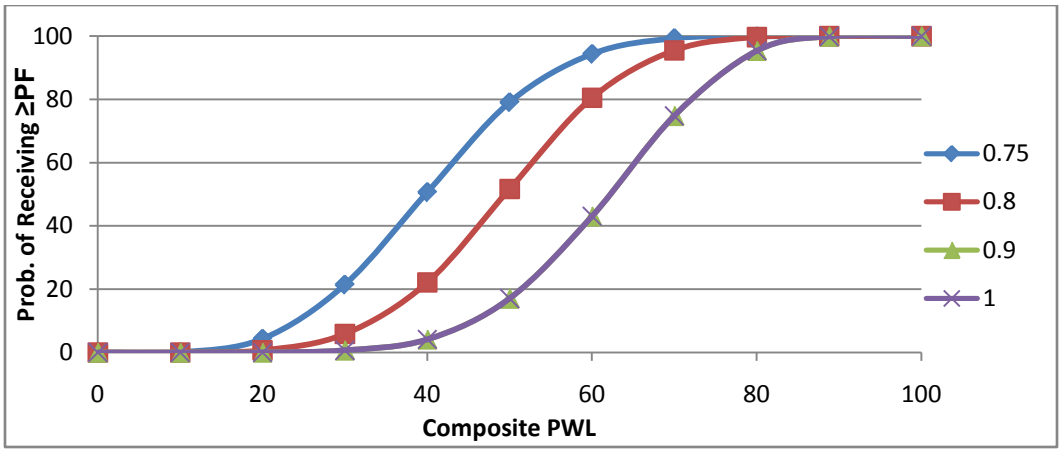

FIGURE C2 EP Curves with Expected PF Using Population Variability Standard Deviation and C = 63 CMPWL (α=1%)

Example analysis: Reducing Population Variability

As indicated previously, based on the population characteristics of the four HMA mixture parameters only 88.7% of the data are within the specification tolerances. Thus, in order to achieve, at the long run, a 90CMPWL (AQL) either the mixture production variability has to be reduced (higher homogeneity during production) reducing thus the population standard deviation, or the specification limits have to be widen (if it is concluded that the existing variability represents the best achievable levels of production). As shown in the example before, a reduction of 3.6% in the population standard deviation is needed in order achieve a 90CMPWL with the current tolerances. Using this value the simulation analysis were carried out with this methodology and the results are summarized in Tables B4-B5, and Figures B3-B4. As it can be seen from the results of the simulation analysis, by setting C equal to 73PWL the α and β are estimated to be 1.5% and 1% respectively. These values may represent a more balanced set of agency and contractor risk than when the C is set to be equal to AQL (90%).

When the C value of 63 CMPWL was used the risk to the agency (β) increased to 5% where the contractor is bearing no risk at all. Therefore, having C = 73PWL results in a more balanced set of risks.

TABLE C4 Probability of Receiving ≥PF at Different CMPWL by Reducing Population Variability and with C = 73CMPWL

PWL	Prob of Receiving >=PF			
	0.75	0.8	0.9	1
0	0	0	0	0
10	0.1	0.01	0	0
20	4.11	0.61	0.02	0.01
30	21.23	6.11	0.2	0.11
40	52.01	23.47	1.42	0.89
50	79.16	50.96	6.76	4.3
60	94.35	80.1	23.86	17.05
70	99.23	95.1	51.74	42.51
80	99.92	99.51	84.21	76.54
90	100	100	99.36	98.44
100	100	100	100	100

Note1: 10000 iterations at each PWL
Note2: The values at 100PWL are interpolated

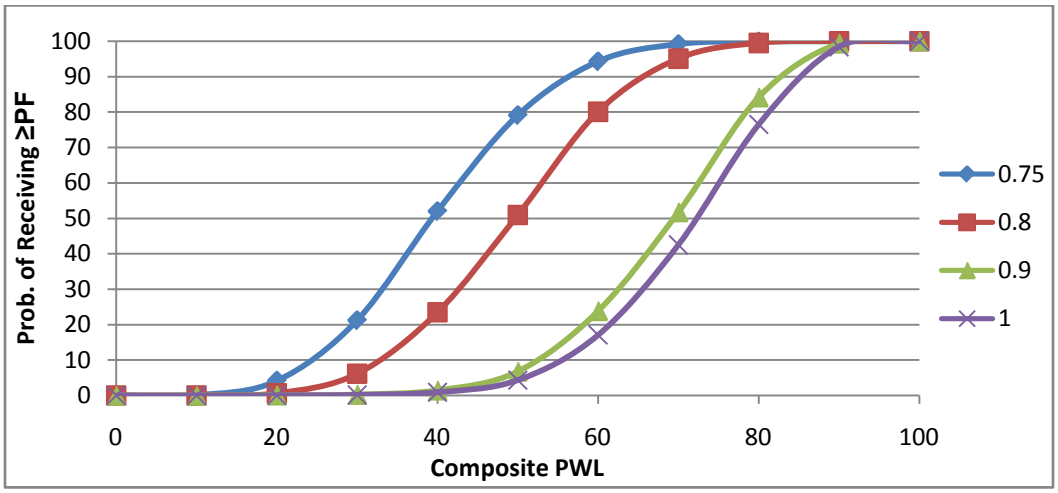

FIGURE C3 EP Curves with Expected PF Using Reduced Population Variability and C Value of c= 73 CMPWL

TABLE C5 Probability of Receiving ≥PF at Different CMPWL by Reducing Population Variability and with C = 63CMPWL

PWL	Prob of Receiving >=PF			
	0.75	0.8	0.9	1
0	0	0	0	0
10	0.1	0	0	0
20	3.93	0.49	0.02	0.02
30	22.43	6.25	0.66	0.66
40	51.02	22.75	4.62	4.62
50	78.44	50.23	16.16	16.16
60	93.8	79	41.85	41.85
70	99.36	95.57	73.84	73.84
80	99.94	99.62	94.93	94.93
90	100	100	99.97	99.97
100	100	100	100	100

Note1: 10000 iterations at each PWL
Note2: The values at 100PWL are interpolated

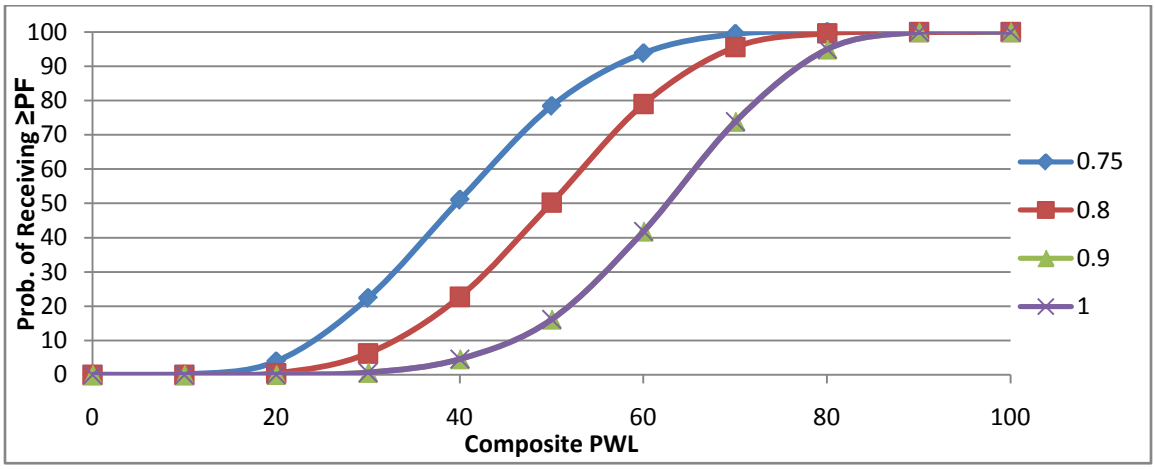

FIGURE C4 EP Curves with Expected PF Using Reduced Population Variability and C Value of C= 63 CMPWL