STATE HIGHWAY ADMINISTRATION

RESEARCH REPORT

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

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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.

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Research Project SP708B4E

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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)

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 \textit{Volumetric Requirements for Superpave Mix Design} (2006) represent the best current thinking on enhancing durability of Superpave mixes.\(^2\)

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\(^1\) 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 ($N_{\text{design}}$), 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., $N_{\text{design}}$). 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 ($N_{\text{design}}$), 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).
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).
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.
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 $N_{\text{design}}$ (FIGURE 2.5; compare with FIGURE 2.3). Reducing design air voids or $N_{\text{design}}$ 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 $N_{\text{design}}$) 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 $N_{\text{design}}$ on Rut Resistance at 4% Design Air Voids and 7% In-Place Air Voids (Christensen and Bonaquist, 2006)](image)

**FIGURE 2.5 Effect of Binder Grade and $N_{\text{design}}$ 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).
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°C, Christensen and Bonquist 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 FM300 for a MAAT of 15.6°C (Christensen and Bonaquist, 2006)](image)

**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 \(N_{\text{design}}\) 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 \(N_{\text{design}}\) 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\(_{\text{design}}\) Values for Superpave Mix Design](image)

<table>
<thead>
<tr>
<th>Design Level</th>
<th>20-Year Design Traffic (Million ESALs)</th>
<th>AASHTO M323 (N_{\text{design}})</th>
<th>MD SHA 904 (N_{\text{design}})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;0.3</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td>0.3 to &lt;3</td>
<td>75</td>
<td>65</td>
</tr>
<tr>
<td>3</td>
<td>3 to &lt;10</td>
<td>100 (75)(^*)</td>
<td>80</td>
</tr>
<tr>
<td>4</td>
<td>10 to &lt;30</td>
<td>100</td>
<td>80</td>
</tr>
<tr>
<td>5</td>
<td>(\geq30)</td>
<td>125</td>
<td>100</td>
</tr>
</tbody>
</table>

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

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 $N_{\text{design}}$ 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 $N_{\text{design}}$ 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 $N_{\text{design}}$ 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 $N_{\text{design}}$ 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 \( N_{\text{design}} \) 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

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

\[ \Delta_{GDOT} = X_{GDOT} - X_{JMF} \]  \hspace{1cm} \text{EQUATION 2.1}  \\
\[ \Delta_{CONT} = X_{CONT} - X_{JMF} \]  \hspace{1cm} \text{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)**

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

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

<table>
<thead>
<tr>
<th>Property</th>
<th>$n$</th>
<th>$S^2_{\text{GDOT}}$, %</th>
<th>$S^2_{\text{CONT}}$, %</th>
<th>Difference</th>
<th>$p$-Value</th>
<th>Pay</th>
</tr>
</thead>
<tbody>
<tr>
<td>% pass 1&quot;</td>
<td>395</td>
<td>1.527</td>
<td>1.363</td>
<td>NSD</td>
<td>0.131</td>
<td>NO</td>
</tr>
<tr>
<td>% pass ¾&quot;</td>
<td>791</td>
<td>4.410</td>
<td>3.831</td>
<td>NSD</td>
<td>0.024</td>
<td>NO</td>
</tr>
<tr>
<td>% pass ½&quot;</td>
<td>1067</td>
<td>9.343</td>
<td>6.576</td>
<td>SD</td>
<td>&lt;0.001</td>
<td>YES</td>
</tr>
<tr>
<td>% pass ⅜&quot;</td>
<td>953</td>
<td>8.479</td>
<td>5.545</td>
<td>SD</td>
<td>&lt;0.001</td>
<td>YES</td>
</tr>
<tr>
<td>% pass #4</td>
<td>402</td>
<td>9.450</td>
<td>8.606</td>
<td>NSD</td>
<td>0.175</td>
<td>YES</td>
</tr>
<tr>
<td>% pass #8</td>
<td>1142</td>
<td>8.673</td>
<td>6.561</td>
<td>SD</td>
<td>&lt;0.001</td>
<td>YES</td>
</tr>
<tr>
<td>% pass #50</td>
<td>282</td>
<td>3.971</td>
<td>4.004</td>
<td>NSD</td>
<td>0.472</td>
<td>NO</td>
</tr>
<tr>
<td>% pass #200</td>
<td>1141</td>
<td>1.137</td>
<td>0.791</td>
<td>SD</td>
<td>&lt;0.001</td>
<td>NO</td>
</tr>
<tr>
<td>% asphalt</td>
<td>1135</td>
<td>0.088</td>
<td>0.045</td>
<td>SD</td>
<td>&lt;0.001</td>
<td>YES</td>
</tr>
</tbody>
</table>
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>
<thead>
<tr>
<th>Property</th>
<th>Projects</th>
<th>Projects with Larger GDOT Means</th>
<th>Projects with Significant Differences</th>
<th>Projects with Larger GDOT Means</th>
<th>Projects with Significant Differences</th>
<th>Projects with Larger GDOT Variances</th>
<th>Projects with Significant Differences</th>
<th>Projects with Larger GDOT Variances</th>
</tr>
</thead>
<tbody>
<tr>
<td>% asphalt</td>
<td>41</td>
<td>27 (66%)</td>
<td>1 (2%)</td>
<td>0</td>
<td>35 (85%)</td>
<td>1 (2%)</td>
<td>1 (2%)</td>
<td>1 (2%)</td>
</tr>
<tr>
<td>% pass $\frac{1}{2}$</td>
<td>34</td>
<td>15 (44%)</td>
<td>0</td>
<td>0</td>
<td>20 (59%)</td>
<td>2 (6%)</td>
<td>2 (6%)</td>
<td>2 (6%)</td>
</tr>
<tr>
<td>% pass #200</td>
<td>45</td>
<td>21 (47%)</td>
<td>2 (4%)</td>
<td>2 (4%)</td>
<td>34 (76%)</td>
<td>3 (7%)</td>
<td>3 (7%)</td>
<td>3 (7%)</td>
</tr>
</tbody>
</table>

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.

\[
Q_L = \frac{X - LSL}{s} \quad \text{EQUATION 2.3}
\]

and

\[
Q_U = \frac{USL - X}{s} \quad \text{EQUATION 2.4}
\]

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 (\(\text{PWL}_T = \text{PWL}_U + \text{PWL}_L - 100\)).

Where:

- \(\text{PWL}_U\) = percent below the upper specification limit (based on \(Q_U\))
- \(\text{PWL}_L\) = percent above the lower specification limit (based on \(Q_L\))
- \(\text{PWL}_T\) = 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

\[
\text{AAD} = \frac{\sum |X_i - T|}{n} \quad \text{EQUATION 2.5}
\]

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.

\[
CI = \sqrt{\frac{\sum(x_i - T)^2}{n}} \tag{EQUATION 2.6}
\]

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 values 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>
<thead>
<tr>
<th>Acceptance Quality Characteristic</th>
<th>Standard Deviation Assumed in Initial PWL Specification</th>
<th>Standard Deviation Selected for Revised QA Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asphalt content</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surface</td>
<td>0.25</td>
<td>0.22</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0.29</td>
<td>0.26</td>
</tr>
<tr>
<td>Air voids</td>
<td>0.76</td>
<td>0.70</td>
</tr>
<tr>
<td>VMA</td>
<td>0.76</td>
<td>0.70</td>
</tr>
<tr>
<td>Density</td>
<td>1.21</td>
<td>1.09</td>
</tr>
</tbody>
</table>

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)

<table>
<thead>
<tr>
<th>Acceptance Quality Characteristic</th>
<th>Initial Specification Limits, %</th>
<th>Derivation of Tolerance (1.6456)</th>
<th>New Specification Limits, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>JMF ± 0.41</td>
<td>1.645 × 0.22 = 0.36</td>
<td>JMF ± 0.36</td>
</tr>
<tr>
<td>Surface</td>
<td>JMF ± 0.48</td>
<td>1.645 × 0.26 = 0.43</td>
<td>JMF ± 0.43</td>
</tr>
<tr>
<td>Intermediate</td>
<td>JMF ± 1.25</td>
<td>1.645 × 0.70 = 1.15</td>
<td>JMF ± 1.15</td>
</tr>
<tr>
<td>AV</td>
<td>JMF ± 1.25</td>
<td>1.645 × 0.70 = 1.15</td>
<td>JMF ± 1.15</td>
</tr>
<tr>
<td>VMA</td>
<td>JMF ± 1.25</td>
<td>1.645 × 1.09 = 1.80</td>
<td>92.2–96.0</td>
</tr>
<tr>
<td>Density</td>
<td>92–96</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 ($\alpha$): 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)
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:

\[
PF = 55 + (0.5 \times PWL)
\]  

**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:

\[
LPF = 0.25(\text{PF}_{\text{AC}}) + 0.30(\text{PF}_{\text{AV}}) + 0.10(\text{PF}_{\text{VMA}}) + 0.35(\text{PF}_{\text{DEN}}) \quad \text{EQUATION 2.8}
\]

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)

<table>
<thead>
<tr>
<th>Population PWL</th>
<th>One QC&lt;sup&gt;a&lt;/sup&gt; ( n = 3 )</th>
<th>One QC&lt;sup&gt;a&lt;/sup&gt; ( n = 4 )</th>
<th>One QC&lt;sup&gt;a&lt;/sup&gt; ( n = 5 )</th>
<th>Four QC&lt;sup&gt;b&lt;/sup&gt; ( n = 3 )</th>
<th>Four QC&lt;sup&gt;b&lt;/sup&gt; ( n = 4 )</th>
<th>Four QC&lt;sup&gt;b&lt;/sup&gt; ( n = 5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>95</td>
<td>0.014</td>
<td>0.006</td>
<td>0.001</td>
<td>0.055</td>
<td>0.024</td>
<td>0.004</td>
</tr>
<tr>
<td>90</td>
<td>0.050</td>
<td>0.032</td>
<td>0.007</td>
<td>0.219</td>
<td>0.122</td>
<td>0.028</td>
</tr>
<tr>
<td>85</td>
<td>0.107</td>
<td>0.085</td>
<td>0.045</td>
<td>0.364</td>
<td>0.259</td>
<td>0.168</td>
</tr>
<tr>
<td>80</td>
<td>0.184</td>
<td>0.120</td>
<td>0.114</td>
<td>0.557</td>
<td>0.400</td>
<td>0.384</td>
</tr>
<tr>
<td>75</td>
<td>0.313</td>
<td>0.226</td>
<td>0.187</td>
<td>0.777</td>
<td>0.641</td>
<td>0.593</td>
</tr>
<tr>
<td>70</td>
<td>0.363</td>
<td>0.321</td>
<td>0.288</td>
<td>0.835</td>
<td>0.787</td>
<td>0.743</td>
</tr>
<tr>
<td>65</td>
<td>0.486</td>
<td>0.434</td>
<td>0.422</td>
<td>0.930</td>
<td>0.857</td>
<td>0.888</td>
</tr>
<tr>
<td>60</td>
<td>0.570</td>
<td>0.557</td>
<td>0.552</td>
<td>0.966</td>
<td>0.961</td>
<td>0.960</td>
</tr>
<tr>
<td>55</td>
<td>0.630</td>
<td>0.666</td>
<td>0.679</td>
<td>0.981</td>
<td>0.988</td>
<td>0.989</td>
</tr>
<tr>
<td>50</td>
<td>0.727</td>
<td>0.725</td>
<td>0.768</td>
<td>0.994</td>
<td>0.994</td>
<td>0.997</td>
</tr>
<tr>
<td>45</td>
<td>0.789</td>
<td>0.817</td>
<td>0.864</td>
<td>0.998</td>
<td>0.999</td>
<td>1.000</td>
</tr>
<tr>
<td>40</td>
<td>0.847</td>
<td>0.866</td>
<td>0.906</td>
<td>0.999</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>35</td>
<td>0.898</td>
<td>0.934</td>
<td>0.952</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>30</td>
<td>0.938</td>
<td>0.945</td>
<td>0.969</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>25</td>
<td>0.964</td>
<td>0.979</td>
<td>0.990</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>20</td>
<td>0.977</td>
<td>0.988</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>15</td>
<td>0.992</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>10</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>5</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>0</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

<sup>a</sup>With one quality characteristic.<br><sup>b</sup>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)

<table>
<thead>
<tr>
<th></th>
<th>AC</th>
<th>AV</th>
<th>VMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>—&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.247</td>
<td>0.856</td>
</tr>
<tr>
<td>AV</td>
<td>0.247</td>
<td>—&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.691</td>
</tr>
<tr>
<td>VMA</td>
<td>0.856</td>
<td>0.691</td>
<td>—&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<sup>a</sup>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>
<thead>
<tr>
<th>Quality Characteristics Simulated</th>
<th>Correlation Coefficient</th>
<th>Average Composite Payment Factor&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Standard Deviation of Composite Payment Factors&lt;sup&gt;a&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC and AV</td>
<td>0.000</td>
<td>55.04</td>
<td>2.12</td>
</tr>
<tr>
<td>AC and AV</td>
<td>0.247</td>
<td>55.02</td>
<td>2.18</td>
</tr>
<tr>
<td>AC and VMA</td>
<td>0.000</td>
<td>35.01</td>
<td>1.46</td>
</tr>
<tr>
<td>AC and VMA</td>
<td>0.856</td>
<td>35.04</td>
<td>1.78</td>
</tr>
<tr>
<td>AV and VMA</td>
<td>0.000</td>
<td>40.04</td>
<td>1.72</td>
</tr>
<tr>
<td>AV and VMA</td>
<td>0.691</td>
<td>39.95</td>
<td>1.98</td>
</tr>
</tbody>
</table>

<sup>a</sup>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

<table>
<thead>
<tr>
<th></th>
<th>Small Sample Size</th>
<th>Medium Sample Size</th>
<th>Large Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>t Tests</td>
<td>F Test</td>
<td>t Tests</td>
</tr>
<tr>
<td>Accepted</td>
<td>100%</td>
<td>83%</td>
<td>88%</td>
</tr>
<tr>
<td>Rejected</td>
<td>0%</td>
<td>17%</td>
<td>13%</td>
</tr>
</tbody>
</table>

#### 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>
<thead>
<tr>
<th>MixSize</th>
<th>MixType</th>
<th>Property</th>
<th>$t$ Test</th>
<th>F Test</th>
<th># of Observations</th>
<th>Mean</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>QA</td>
<td>QC</td>
<td>QA</td>
<td>QC</td>
<td>QA</td>
<td>QC</td>
<td>QA</td>
<td>QC</td>
</tr>
<tr>
<td>12 G</td>
<td>AC</td>
<td>Rejected</td>
<td>Rejected</td>
<td>636</td>
<td>870</td>
<td>6.4074</td>
<td>6.5140</td>
</tr>
<tr>
<td>12 H</td>
<td>AC</td>
<td>Rejected</td>
<td>Rejected</td>
<td>311</td>
<td>429</td>
<td>4.9040</td>
<td>4.8390</td>
</tr>
</tbody>
</table>

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 subplot number between the QA and QC may have been different. The latter case required selecting projects that had the same number of subplot 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

<table>
<thead>
<tr>
<th>Mix Type</th>
<th>Property</th>
<th># of T Test</th>
<th>T Test</th>
<th>F Test</th>
<th>% T Test Accepted</th>
<th>% T Test Rejected</th>
<th>% F Test Accepted</th>
<th>% F Test Rejected</th>
</tr>
</thead>
<tbody>
<tr>
<td>G</td>
<td>ALL</td>
<td>139</td>
<td>2738</td>
<td>3816</td>
<td>51.8%</td>
<td>48.2%</td>
<td>131</td>
<td>67.9%</td>
</tr>
<tr>
<td>H</td>
<td>ALL</td>
<td>423</td>
<td>2636</td>
<td>3762</td>
<td>80.6%</td>
<td>19.4%</td>
<td>380</td>
<td>82.6%</td>
</tr>
<tr>
<td>R</td>
<td>ALL</td>
<td>1204</td>
<td>8165</td>
<td>10577</td>
<td>74.4%</td>
<td>25.6%</td>
<td>1028</td>
<td>75.7%</td>
</tr>
<tr>
<td>S</td>
<td>ALL</td>
<td>67</td>
<td>352</td>
<td>441</td>
<td>82.1%</td>
<td>17.9%</td>
<td>60</td>
<td>86.7%</td>
</tr>
<tr>
<td>V</td>
<td>ALL</td>
<td>637</td>
<td>4830</td>
<td>6011</td>
<td>74.7%</td>
<td>25.3%</td>
<td>563</td>
<td>76.0%</td>
</tr>
<tr>
<td>ALL</td>
<td>ALL</td>
<td>632</td>
<td>4750</td>
<td>6254</td>
<td>72.0%</td>
<td>28.0%</td>
<td>559</td>
<td>74.8%</td>
</tr>
<tr>
<td>ALL</td>
<td>4.75</td>
<td>612</td>
<td>4664</td>
<td>6127</td>
<td>80.6%</td>
<td>19.4%</td>
<td>533</td>
<td>74.1%</td>
</tr>
<tr>
<td>ALL</td>
<td>2.36</td>
<td>608</td>
<td>4660</td>
<td>6127</td>
<td>84.0%</td>
<td>16.0%</td>
<td>520</td>
<td>77.3%</td>
</tr>
<tr>
<td>ALL</td>
<td>0.075</td>
<td>618</td>
<td>4647</td>
<td>6099</td>
<td>61.7%</td>
<td>38.3%</td>
<td>550</td>
<td>81.1%</td>
</tr>
</tbody>
</table>

** Table includes all the data.
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.
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
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

<table>
<thead>
<tr>
<th>Mix Type</th>
<th>Property</th>
<th>Mix Band</th>
<th>QA_N</th>
<th>QC_N</th>
<th>% of T_Test Accepted</th>
<th>% Test Rejected</th>
<th>% of f_Test Accepted</th>
<th>% Rejected</th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>AC</td>
<td>09</td>
<td>387</td>
<td>504</td>
<td>26</td>
<td>62.0%</td>
<td>36.0%</td>
<td>25</td>
</tr>
<tr>
<td>H</td>
<td>AC</td>
<td>12</td>
<td>225</td>
<td>345</td>
<td>16</td>
<td>87.5%</td>
<td>12.5%</td>
<td>14</td>
</tr>
<tr>
<td>H</td>
<td>AC</td>
<td>19</td>
<td>62</td>
<td>101</td>
<td>3</td>
<td>100.0%</td>
<td>0.0%</td>
<td>1</td>
</tr>
<tr>
<td>H</td>
<td>4.75</td>
<td>09</td>
<td>382</td>
<td>502</td>
<td>27</td>
<td>81.0%</td>
<td>19.0%</td>
<td>25</td>
</tr>
<tr>
<td>H</td>
<td>4.75</td>
<td>12</td>
<td>207</td>
<td>326</td>
<td>16</td>
<td>81.3%</td>
<td>18.7%</td>
<td>15</td>
</tr>
<tr>
<td>H</td>
<td>4.75</td>
<td>19</td>
<td>57</td>
<td>99</td>
<td>2</td>
<td>100.0%</td>
<td>0.0%</td>
<td>1</td>
</tr>
<tr>
<td>H</td>
<td>2.36</td>
<td>09</td>
<td>378</td>
<td>496</td>
<td>25</td>
<td>88.0%</td>
<td>12.0%</td>
<td>25</td>
</tr>
<tr>
<td>H</td>
<td>2.36</td>
<td>12</td>
<td>207</td>
<td>326</td>
<td>16</td>
<td>87.5%</td>
<td>12.5%</td>
<td>12</td>
</tr>
<tr>
<td>H</td>
<td>2.36</td>
<td>19</td>
<td>57</td>
<td>99</td>
<td>2</td>
<td>100.0%</td>
<td>0.0%</td>
<td>1</td>
</tr>
<tr>
<td>H</td>
<td>0.075</td>
<td>09</td>
<td>377</td>
<td>500</td>
<td>26</td>
<td>84.6%</td>
<td>15.4%</td>
<td>25</td>
</tr>
<tr>
<td>H</td>
<td>0.075</td>
<td>12</td>
<td>205</td>
<td>324</td>
<td>16</td>
<td>87.5%</td>
<td>12.5%</td>
<td>15</td>
</tr>
<tr>
<td>H</td>
<td>0.075</td>
<td>19</td>
<td>57</td>
<td>100</td>
<td>3</td>
<td>100.0%</td>
<td>0.0%</td>
<td>1</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Mix Type</th>
<th>Property</th>
<th>Mix Band</th>
<th>QA_N</th>
<th>QC_N</th>
<th>% of T_Test Accepted</th>
<th>% Test Rejected</th>
<th>% of f_Test Accepted</th>
<th>% Rejected</th>
</tr>
</thead>
<tbody>
<tr>
<td>G</td>
<td>AC</td>
<td>09</td>
<td>99</td>
<td>133</td>
<td>6</td>
<td>65.5%</td>
<td>34.5%</td>
<td>27</td>
</tr>
<tr>
<td>G</td>
<td>AC</td>
<td>12</td>
<td>587</td>
<td>827</td>
<td>29</td>
<td>84.6%</td>
<td>15.4%</td>
<td>25</td>
</tr>
<tr>
<td>G</td>
<td>AC</td>
<td>19</td>
<td>NO DATA</td>
<td>NO DATA</td>
<td>NO DATA</td>
<td>50.0%</td>
<td>50.0%</td>
<td>6</td>
</tr>
<tr>
<td>G</td>
<td>4.75</td>
<td>09</td>
<td>98</td>
<td>133</td>
<td>6</td>
<td>50.0%</td>
<td>50.0%</td>
<td>6</td>
</tr>
<tr>
<td>G</td>
<td>4.75</td>
<td>12</td>
<td>587</td>
<td>819</td>
<td>28</td>
<td>46.4%</td>
<td>53.6%</td>
<td>27</td>
</tr>
<tr>
<td>G</td>
<td>4.75</td>
<td>19</td>
<td>NO DATA</td>
<td>NO DATA</td>
<td>NO DATA</td>
<td>50.0%</td>
<td>50.0%</td>
<td>6</td>
</tr>
<tr>
<td>G</td>
<td>2.36</td>
<td>09</td>
<td>98</td>
<td>133</td>
<td>6</td>
<td>66.7%</td>
<td>33.3%</td>
<td>5</td>
</tr>
<tr>
<td>G</td>
<td>2.36</td>
<td>12</td>
<td>587</td>
<td>820</td>
<td>29</td>
<td>62.1%</td>
<td>37.9%</td>
<td>27</td>
</tr>
<tr>
<td>G</td>
<td>2.36</td>
<td>19</td>
<td>NO DATA</td>
<td>NO DATA</td>
<td>NO DATA</td>
<td>50.0%</td>
<td>50.0%</td>
<td>6</td>
</tr>
<tr>
<td>G</td>
<td>0.075</td>
<td>09</td>
<td>98</td>
<td>133</td>
<td>6</td>
<td>53.3%</td>
<td>46.7%</td>
<td>6</td>
</tr>
<tr>
<td>G</td>
<td>0.075</td>
<td>12</td>
<td>587</td>
<td>816</td>
<td>29</td>
<td>34.5%</td>
<td>65.5%</td>
<td>27</td>
</tr>
<tr>
<td>G</td>
<td>0.075</td>
<td>19</td>
<td>NO DATA</td>
<td>NO DATA</td>
<td>NO DATA</td>
<td>50.0%</td>
<td>50.0%</td>
<td>6</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Mix Type</th>
<th>Property</th>
<th>Mix Band</th>
<th>QA_N</th>
<th>QC_N</th>
<th>% of T_Test Accepted</th>
<th>% Test Rejected</th>
<th>% of f_Test Accepted</th>
<th>% Rejected</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>AC</td>
<td>09</td>
<td>8</td>
<td>12</td>
<td>3</td>
<td>66.7%</td>
<td>33.3%</td>
<td>2</td>
</tr>
<tr>
<td>S</td>
<td>AC</td>
<td>12</td>
<td>64</td>
<td>79</td>
<td>11</td>
<td>65.5%</td>
<td>34.5%</td>
<td>10</td>
</tr>
<tr>
<td>S</td>
<td>AC</td>
<td>19</td>
<td>13</td>
<td>17</td>
<td>4</td>
<td>100.0%</td>
<td>0.0%</td>
<td>4</td>
</tr>
<tr>
<td>S</td>
<td>4.75</td>
<td>09</td>
<td>7</td>
<td>10</td>
<td>2</td>
<td>100.0%</td>
<td>0.0%</td>
<td>1</td>
</tr>
<tr>
<td>S</td>
<td>4.75</td>
<td>12</td>
<td>64</td>
<td>79</td>
<td>11</td>
<td>81.8%</td>
<td>18.2%</td>
<td>9</td>
</tr>
<tr>
<td>S</td>
<td>4.75</td>
<td>19</td>
<td>11</td>
<td>15</td>
<td>4</td>
<td>75.0%</td>
<td>25.0%</td>
<td>4</td>
</tr>
<tr>
<td>S</td>
<td>2.36</td>
<td>09</td>
<td>7</td>
<td>10</td>
<td>2</td>
<td>100.0%</td>
<td>0.0%</td>
<td>2</td>
</tr>
<tr>
<td>S</td>
<td>2.36</td>
<td>12</td>
<td>64</td>
<td>79</td>
<td>11</td>
<td>90.9%</td>
<td>9.1%</td>
<td>10</td>
</tr>
<tr>
<td>S</td>
<td>2.36</td>
<td>19</td>
<td>11</td>
<td>15</td>
<td>3</td>
<td>100.0%</td>
<td>0.0%</td>
<td>3</td>
</tr>
<tr>
<td>S</td>
<td>0.075</td>
<td>09</td>
<td>7</td>
<td>10</td>
<td>2</td>
<td>50.0%</td>
<td>50.0%</td>
<td>2</td>
</tr>
<tr>
<td>S</td>
<td>0.075</td>
<td>12</td>
<td>64</td>
<td>79</td>
<td>11</td>
<td>63.6%</td>
<td>36.4%</td>
<td>10</td>
</tr>
<tr>
<td>S</td>
<td>0.075</td>
<td>19</td>
<td>13</td>
<td>17</td>
<td>4</td>
<td>75.0%</td>
<td>25.0%</td>
<td>4</td>
</tr>
</tbody>
</table>
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

$y = 0.832x + 0.961$

$R^2 = 0.247$
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 (\(\alpha\)) and the buyer’s risk (\(\beta\)) 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 \(\alpha\) and \(\beta\) 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 properties of the gap graded mixtures. The table includes information on the ProjectID, JMFID, lot number, and number of sublots, n, within a lot.

<table>
<thead>
<tr>
<th>Property</th>
<th>ProjectID</th>
<th>JMFID</th>
<th>Lot#</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.075</td>
<td>GA6445177</td>
<td>W13512G4D01F</td>
<td>2</td>
<td>9</td>
</tr>
<tr>
<td>2.36</td>
<td>FT458M80</td>
<td>N13812G4F01F</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>4.75</td>
<td>BA481B51</td>
<td>N08312G4F02F</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>AC</td>
<td>AA416B51</td>
<td>N05109G4F01F</td>
<td>1</td>
<td>9</td>
</tr>
</tbody>
</table>

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.
As illustrated in figures 4.1 through 4.4, for a sample size \( n = 6 \), the \( \alpha \) and \( \beta \) 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.
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>
<thead>
<tr>
<th>Property</th>
<th>Tolerance</th>
<th>α @ AQL=90%</th>
<th>β @ RQL=40%</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.075</td>
<td>± 2</td>
<td>0.0%</td>
<td>26.5%</td>
</tr>
<tr>
<td>2.36</td>
<td>± 5</td>
<td>0.1%</td>
<td>26.8%</td>
</tr>
<tr>
<td>4.75</td>
<td>± 5</td>
<td>0.0%</td>
<td>27.6%</td>
</tr>
<tr>
<td>AC</td>
<td>± 0.5</td>
<td>0.1%</td>
<td>26.3%</td>
</tr>
</tbody>
</table>

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%**.

<table>
<thead>
<tr>
<th>Property</th>
<th>Tolerance</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.075</td>
<td>0.9</td>
</tr>
<tr>
<td>2.36</td>
<td>1.2</td>
</tr>
<tr>
<td>4.75</td>
<td>2.9</td>
</tr>
<tr>
<td>AC</td>
<td>0.15</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>Property</th>
<th>0.075</th>
<th>2.36</th>
<th>4.75</th>
<th>AC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.075</td>
<td>1</td>
<td>0.338</td>
<td>0.208</td>
<td>0.242</td>
</tr>
<tr>
<td>2.36</td>
<td>0.338</td>
<td>1</td>
<td>0.562</td>
<td>0.261</td>
</tr>
<tr>
<td>4.75</td>
<td>0.208</td>
<td>0.562</td>
<td>1</td>
<td>0.305</td>
</tr>
<tr>
<td>AC</td>
<td>0.242</td>
<td>0.261</td>
<td>0.305</td>
<td>1</td>
</tr>
</tbody>
</table>
TABLE 5.2 Population Characteristics

<table>
<thead>
<tr>
<th>Property</th>
<th>Delta Mean*</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.075</td>
<td>0.992</td>
<td>1.20</td>
</tr>
<tr>
<td>2.36</td>
<td>-0.192</td>
<td>3.88</td>
</tr>
<tr>
<td>4.75</td>
<td>0.066</td>
<td>5.60</td>
</tr>
<tr>
<td>AC</td>
<td>-0.002</td>
<td>0.31</td>
</tr>
</tbody>
</table>

*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.

\[
\begin{align*}
MF &= 0.55 + 0.5CMPWSL \\
\text{if } CMPWSL &\geq 90\% \quad MF = 1 \\
\text{if } CMPWSL &< 40\% \quad MF = 0
\end{align*}
\]

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**
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>
<thead>
<tr>
<th>AC_Tol</th>
<th>%Change</th>
<th>Mean_CM</th>
<th>Mean_MF</th>
<th>% Change CM</th>
<th>% Change MF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100%</td>
<td>92.4</td>
<td>99.7</td>
<td>7%</td>
<td>2.4%</td>
</tr>
<tr>
<td>0.75</td>
<td>50%</td>
<td>91.6</td>
<td>99.5</td>
<td>6%</td>
<td>2.1%</td>
</tr>
<tr>
<td>0.6</td>
<td>20%</td>
<td>89.4</td>
<td>98.7</td>
<td>4%</td>
<td>1.4%</td>
</tr>
<tr>
<td>0.55</td>
<td>10%</td>
<td>88.0</td>
<td>98.2</td>
<td>2%</td>
<td>0.8%</td>
</tr>
<tr>
<td>0.5</td>
<td>0%</td>
<td>86.0</td>
<td>97.4</td>
<td>0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>0.45</td>
<td>-10%</td>
<td>83.6</td>
<td>96.3</td>
<td>-3%</td>
<td>-1.1%</td>
</tr>
<tr>
<td>0.4</td>
<td>-20%</td>
<td>80.7</td>
<td>95.0</td>
<td>-6%</td>
<td>-2.4%</td>
</tr>
<tr>
<td>0.25</td>
<td>-50%</td>
<td>66.9</td>
<td>88.4</td>
<td>-22%</td>
<td>-9.3%</td>
</tr>
</tbody>
</table>
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.
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>
<thead>
<tr>
<th>2.36_Tol</th>
<th>%Change</th>
<th>Mean_CM</th>
<th>Mean_MF</th>
<th>% Change CM</th>
<th>% Change MF</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>100%</td>
<td>87.5</td>
<td>97.9</td>
<td>1.76%</td>
<td>0.40%</td>
</tr>
<tr>
<td>7.5</td>
<td>50%</td>
<td>87.0</td>
<td>97.7</td>
<td>1.13%</td>
<td>0.20%</td>
</tr>
<tr>
<td>6</td>
<td>20%</td>
<td>86.6</td>
<td>97.6</td>
<td>0.71%</td>
<td>0.07%</td>
</tr>
<tr>
<td>5.5</td>
<td>10%</td>
<td>86.4</td>
<td>97.5</td>
<td>0.49%</td>
<td>0.02%</td>
</tr>
<tr>
<td>5</td>
<td>0%</td>
<td>86.0</td>
<td>97.4</td>
<td>0.00%</td>
<td>-0.12%</td>
</tr>
<tr>
<td>4.5</td>
<td>-10%</td>
<td>85.7</td>
<td>97.3</td>
<td>-0.28%</td>
<td>-0.21%</td>
</tr>
<tr>
<td>4</td>
<td>-20%</td>
<td>85.4</td>
<td>97.2</td>
<td>-0.65%</td>
<td>-0.32%</td>
</tr>
<tr>
<td>2.5</td>
<td>-50%</td>
<td>83.9</td>
<td>96.6</td>
<td>-2.45%</td>
<td>-0.90%</td>
</tr>
</tbody>
</table>

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

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.
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%.

\[
\begin{cases}
  MF = 0.55 + 0.5CMPWSL \\
  \text{if } CMPWSL < 40\% \, MF = 0
\end{cases}
\]

EQUATION 5.2

The Composite Mixture PWSL (CMPWSL) is calculated by:

\[
\text{CMPWSL} = \frac{f_1 \text{PWSL}_1 + f_2 \text{PWSL}_2 + f_3 \text{PWSL}_3 + f_4 \text{PWSL}_4}{\Sigma f}
\]

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

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

**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

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

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

<table>
<thead>
<tr>
<th>4.75_Tol</th>
<th>%Change</th>
<th>Mean_CM</th>
<th>Mean_MF</th>
<th>% Change CM</th>
<th>% Change MF</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>100%</td>
<td>87.5</td>
<td>98.8</td>
<td>1.7%</td>
<td>1%</td>
</tr>
<tr>
<td>10.5</td>
<td>50%</td>
<td>87.2</td>
<td>98.6</td>
<td>1.3%</td>
<td>0.5%</td>
</tr>
<tr>
<td>8.4</td>
<td>20%</td>
<td>86.6</td>
<td>98.3</td>
<td>0.7%</td>
<td>0.2%</td>
</tr>
<tr>
<td>7.7</td>
<td>10%</td>
<td>86.2</td>
<td>98.1</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td>7</td>
<td>0%</td>
<td>86.1</td>
<td>98.0</td>
<td>0.0%</td>
<td>-0.1%</td>
</tr>
<tr>
<td>6.3</td>
<td>-10%</td>
<td>85.8</td>
<td>97.9</td>
<td>-0.3%</td>
<td>-0.2%</td>
</tr>
<tr>
<td>5.6</td>
<td>-20%</td>
<td>85.2</td>
<td>97.6</td>
<td>-1.0%</td>
<td>-0.5%</td>
</tr>
<tr>
<td>3.5</td>
<td>-50%</td>
<td>83.9</td>
<td>97.0</td>
<td>-2.5%</td>
<td>-1%</td>
</tr>
</tbody>
</table>
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](image-url)
FIGURE 5.19 Variability in Asphalt Content by Various Plants in Maryland

AC_Virgin
Median = 0.2553, Mean = 0.2693
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).

![AC Distribution (Delta_Average=0.00 & Standard Dev. = 0.31)](image-url)

**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

AC Distribution at RQL (Delta_Average=-0.002 & Standard Dev. = 0.31)

FIGURE 6.7 Distribution of Passing 0.075mm at AQL

0.075 Distribution at AQL (Delta_Average=0.99 & Standard Dev. = 0.80*)

*Note: In order to achieve 90PWL the standard deviation was reduced by 33%
FIGURE 6.8 Distribution of Passing 0.075mm at RQL

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

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

2.36 Distribution at RQL (Delta_Average= -0.19 & Standard Dev. = 3.88)
LSL (-5.0) USL (+5.0)

40 PWL

FIGURE 6.11 Distribution of Passing 4.75mm at AQL

4.75 Distribution at AQL (Delta_Average=0.07 & Standard Dev. = 4.31*)
LSL (-7.0) USL (+7.0)

90 PWL

*Note: In order to achieve 90PWL the standard deviation was reduced by 23%
Figure 6.13 shows the probability of receiving $\geq PF$ (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 $PF \geq 1$ 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

<table>
<thead>
<tr>
<th>Property</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.075</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>CMPWL</th>
<th>Prob of Receiving ≥PF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.1</td>
</tr>
<tr>
<td>20</td>
<td>3.81</td>
</tr>
<tr>
<td>30</td>
<td>21.47</td>
</tr>
<tr>
<td>40</td>
<td>51.11</td>
</tr>
<tr>
<td>50</td>
<td>79.19</td>
</tr>
<tr>
<td>60</td>
<td>94.14</td>
</tr>
<tr>
<td>70</td>
<td>99.04</td>
</tr>
<tr>
<td>80</td>
<td>99.98</td>
</tr>
<tr>
<td>86</td>
<td>100</td>
</tr>
<tr>
<td>88.7</td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

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*

<table>
<thead>
<tr>
<th>CMPWL</th>
<th>EP</th>
</tr>
</thead>
<tbody>
<tr>
<td>100.0</td>
<td>1.05</td>
</tr>
<tr>
<td>90.0</td>
<td>1.00</td>
</tr>
<tr>
<td>88.7</td>
<td>0.99</td>
</tr>
<tr>
<td>80.0</td>
<td>0.95</td>
</tr>
<tr>
<td>70.0</td>
<td>0.89</td>
</tr>
<tr>
<td>60.0</td>
<td>0.81</td>
</tr>
<tr>
<td>50.0</td>
<td>0.65</td>
</tr>
<tr>
<td>40.0</td>
<td>0.41</td>
</tr>
</tbody>
</table>

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 \( \geq PF \) at Different PWL by Reducing Population Variability**

<table>
<thead>
<tr>
<th>PWL</th>
<th>Prob of Receiving ( \geq PF )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.09</td>
</tr>
<tr>
<td>20</td>
<td>3.47</td>
</tr>
<tr>
<td>30</td>
<td>21.9</td>
</tr>
<tr>
<td>40</td>
<td>50.22</td>
</tr>
<tr>
<td>50</td>
<td>78.78</td>
</tr>
<tr>
<td>60</td>
<td>94.19</td>
</tr>
<tr>
<td>70</td>
<td>98.96</td>
</tr>
<tr>
<td>80</td>
<td>99.96</td>
</tr>
<tr>
<td>90</td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

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

Average Pay Factor = 0.40913
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 6.23 shows the probability of receiving $\geq PF$ (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)](image)

<table>
<thead>
<tr>
<th>Property</th>
<th>0.075</th>
<th>2.36</th>
<th>4.75</th>
<th>AC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev.</td>
<td>0.912</td>
<td>1.969</td>
<td>3.507</td>
<td>0.299</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>PWL</th>
<th>0.75</th>
<th>0.8</th>
<th>0.9</th>
<th>1</th>
<th>1.04</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.15</td>
<td>0.01</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>4.06</td>
<td>0.62</td>
<td>0.01</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>30</td>
<td>21.66</td>
<td>5.47</td>
<td>0.22</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>40</td>
<td>51.25</td>
<td>22.98</td>
<td>1.56</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>50</td>
<td>78.08</td>
<td>52.21</td>
<td>7.31</td>
<td>0.13</td>
<td>0</td>
</tr>
<tr>
<td>60</td>
<td>94.75</td>
<td>79.73</td>
<td>22.91</td>
<td>0.85</td>
<td>0.01</td>
</tr>
<tr>
<td>70</td>
<td>99.31</td>
<td>95.36</td>
<td>51.91</td>
<td>5.05</td>
<td>0.25</td>
</tr>
<tr>
<td>80</td>
<td>100</td>
<td>99.63</td>
<td>83.82</td>
<td>20.39</td>
<td>2.17</td>
</tr>
<tr>
<td>90</td>
<td>100</td>
<td>99.99</td>
<td>99.04</td>
<td>57.53</td>
<td>17.25</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

*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)**

<table>
<thead>
<tr>
<th>CMPWL</th>
<th>EP</th>
</tr>
</thead>
<tbody>
<tr>
<td>100.0</td>
<td>1.05</td>
</tr>
<tr>
<td>92.9</td>
<td>1.02</td>
</tr>
<tr>
<td>90.0</td>
<td>1.00</td>
</tr>
<tr>
<td>80.0</td>
<td>0.95</td>
</tr>
<tr>
<td>70.0</td>
<td>0.90</td>
</tr>
<tr>
<td>60.0</td>
<td>0.81</td>
</tr>
<tr>
<td>50.0</td>
<td>0.65</td>
</tr>
<tr>
<td>40.0</td>
<td>0.41</td>
</tr>
</tbody>
</table>

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

Average Pay Factor = 0.40764
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
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>
<thead>
<tr>
<th>Mix</th>
<th>Individual</th>
<th>Lot Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gap Graded</td>
<td>95.78</td>
<td>95.67</td>
</tr>
<tr>
<td></td>
<td>83.43</td>
<td>98.32</td>
</tr>
<tr>
<td>Dense Graded</td>
<td>94.14</td>
<td>94.04</td>
</tr>
<tr>
<td></td>
<td>64.17</td>
<td>71.66</td>
</tr>
</tbody>
</table>

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
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>
<thead>
<tr>
<th>Lot Average % Minimum</th>
<th>No Individual Sublot Below %*</th>
<th>Pay Factor %</th>
</tr>
</thead>
<tbody>
<tr>
<td>94.0</td>
<td>94.0</td>
<td>112.0</td>
</tr>
<tr>
<td>93.8</td>
<td>93.7</td>
<td>111.0</td>
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<tr>
<td>93.6</td>
<td>93.4</td>
<td>110.0</td>
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<td>93.4</td>
<td>93.1</td>
<td>109.0</td>
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<tr>
<td>93.2</td>
<td>92.8</td>
<td>108.0</td>
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<tr>
<td>93.0</td>
<td>92.5</td>
<td>107.0</td>
</tr>
<tr>
<td>92.8</td>
<td>92.2</td>
<td>106.0</td>
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<tr>
<td>92.6</td>
<td>91.9</td>
<td>105.0</td>
</tr>
<tr>
<td>92.4</td>
<td>91.6</td>
<td>104.0</td>
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<td>92.2</td>
<td>91.3</td>
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<td>92.0</td>
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<td>91.8</td>
<td>90.8</td>
<td>101.0</td>
</tr>
<tr>
<td>91.6</td>
<td>90.6</td>
<td>100.0</td>
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<tr>
<td>91.4</td>
<td>90.4</td>
<td>99.0</td>
</tr>
<tr>
<td>91.2</td>
<td>90.2</td>
<td>98.0</td>
</tr>
<tr>
<td>91.0</td>
<td>90.0</td>
<td>97.0</td>
</tr>
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<td>90.8</td>
<td>89.8</td>
<td>96.0</td>
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<td>90.6</td>
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<td>95.0</td>
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<td>90.4</td>
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<td>90.2</td>
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<td>90.0</td>
<td>89.0</td>
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<td>89.8</td>
<td>88.8</td>
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<td>89.4</td>
<td>88.4</td>
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</tr>
<tr>
<td>89.2</td>
<td>88.2</td>
<td>88.0</td>
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<td>89.0</td>
<td>88.0</td>
<td>87.0</td>
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<td>88.6</td>
<td>87.6</td>
<td>85.0</td>
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<tr>
<td>88.4</td>
<td>87.4</td>
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</tr>
<tr>
<td>88.2</td>
<td>87.2</td>
<td>83.0</td>
</tr>
<tr>
<td>88.0</td>
<td>87.0</td>
<td>82.0</td>
</tr>
<tr>
<td>Less than 88.0</td>
<td>87.0</td>
<td>75.0 or rejected by Engineer</td>
</tr>
</tbody>
</table>
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 $N_{\text{design}}$ 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.
REFERENCES

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

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

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)


Turochy R., R. Willis, and F. Parker, “Quality Assurance of Hot-Mix Asphalt Comparison of Contractor Quality Control and Georgia Department of Transportation Data,” Transportation Research Record No. 1946, pp. 47-54, Transportation Research Board of the National Academies, Washington, D.C., 2006


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

```matlab
%SSK
close all
clear
cle
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=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 = [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];
USL=SL;
LSL=-SL;
for k=1:m
T = CORR;
for u=1:1:4
    T(:,u) = T(:,u) * sd(u);
end
```

110
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
    end
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

PWSL(1,j)=PU(1,j)+PL(1,j)-100;

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

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);
Median_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

```matlab
%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;
```
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;
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
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>
<thead>
<tr>
<th>TABLE A1 Example of Effect of Correlation Value on the Average PF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average CMPWL</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>86.2</td>
</tr>
<tr>
<td>86.2</td>
</tr>
<tr>
<td>86.0</td>
</tr>
<tr>
<td>86.2</td>
</tr>
</tbody>
</table>
B. Impact of Reducing Population Variability and/or Modifying Spec Tolerances

### TABLE B1 Effects of Reducing Population Standard Deviation

<table>
<thead>
<tr>
<th>% Reduction in SD&lt;sub&gt;pop&lt;/sub&gt;</th>
<th>at AQL (90CMPWL)</th>
<th>at RQL (40 CMPWL)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Probability of receiving a PF &lt; 1</td>
<td>Average PF</td>
</tr>
<tr>
<td>0.0%</td>
<td>N/A</td>
<td>0.01</td>
</tr>
<tr>
<td>3.6%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>5.0%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>10.0%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>20.0%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>35.0%</td>
<td>0.41</td>
<td>1.00</td>
</tr>
<tr>
<td>50.0%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
</tbody>
</table>

### TABLE B2 Effects of Increasing Spec Tolerances

<table>
<thead>
<tr>
<th>% Increase in Tolerance</th>
<th>at AQL (90CMPWL)</th>
<th>at RQL (40 CMPWL)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Probability of receiving a PF &lt; 1</td>
<td>Average PF</td>
</tr>
<tr>
<td>0.0%</td>
<td>N/A</td>
<td>0.01</td>
</tr>
<tr>
<td>3.6%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>5.0%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>10.0%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>20.0%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>35.0%</td>
<td>0.40</td>
<td>1.00</td>
</tr>
<tr>
<td>50.0%</td>
<td>0.41</td>
<td>1.00</td>
</tr>
</tbody>
</table>
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 \( \alpha \) 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 \( \alpha \) risk, \( z(\alpha_c) \). This is just the cumulative normal probability value associated with the primary \( \alpha \) 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 \( \alpha \) 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**

<table>
<thead>
<tr>
<th>Pay Factor</th>
<th>( n=3 )</th>
<th>( n=4 )</th>
<th>( n=5 )</th>
<th>( n=6 )</th>
<th>( n=7 )</th>
<th>( n=8 )</th>
<th>( n=9 )</th>
<th>( n=10 )</th>
<th>( n=11 )</th>
<th>( n=12 )</th>
<th>( n=13 )</th>
<th>( n=14 )</th>
<th>( n=15 )</th>
<th>( n=16 )</th>
<th>( n=17 )</th>
<th>( n=18 )</th>
<th>( n=19 )</th>
<th>( n=20 )</th>
<th>( n=21 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Required Quality Level for a Given Sample Size (n) and a Given Pay Factor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

*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 $\alpha$ 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 $\alpha$ risk of 5% are shown in Table B2 and Figure B1. The $\alpha$ (equal to 1-97.88) and $\beta$ (equal to 0.84) risks are calculated based on the values highlighted in Table B2.

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

**TABLE C2 Probability of Receiving $\geq$PF at Different CMPWL Using Population Characteristics & $C = 73$CMPWL ($\alpha=5\%$)**

<table>
<thead>
<tr>
<th>PWL</th>
<th>Prob of Receiving $\geq$PF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.14</td>
</tr>
<tr>
<td>20</td>
<td>4.20</td>
</tr>
<tr>
<td>30</td>
<td>22.37</td>
</tr>
<tr>
<td>40</td>
<td>51.18</td>
</tr>
<tr>
<td>50</td>
<td>78.58</td>
</tr>
<tr>
<td>60</td>
<td>94.47</td>
</tr>
<tr>
<td>70</td>
<td>99.26</td>
</tr>
<tr>
<td>80</td>
<td>99.97</td>
</tr>
<tr>
<td>88.95</td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

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 ($\alpha=5\%$)

TABLE C3 Probability of Receiving $\geq$PF at Different CMPWL Using Population Characteristics and C = 63CMPWL ($\alpha=1\%$)

<table>
<thead>
<tr>
<th>CMPWL</th>
<th>Prob of Receiving $\geq$PF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.09</td>
</tr>
<tr>
<td>20</td>
<td>4.33</td>
</tr>
<tr>
<td>30</td>
<td>21.45</td>
</tr>
<tr>
<td>40</td>
<td>50.64</td>
</tr>
<tr>
<td>50</td>
<td>79.08</td>
</tr>
<tr>
<td>60</td>
<td>94.38</td>
</tr>
<tr>
<td>70</td>
<td>99.29</td>
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<tr>
<td>80</td>
<td>99.96</td>
</tr>
<tr>
<td>88.781</td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>PWL</th>
<th>Prob of Receiving &gt;=PF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.1</td>
</tr>
<tr>
<td>20</td>
<td>4.11</td>
</tr>
<tr>
<td>30</td>
<td>21.23</td>
</tr>
<tr>
<td>40</td>
<td>52.01</td>
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<tr>
<td>50</td>
<td>79.16</td>
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<tr>
<td>60</td>
<td>94.35</td>
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<tr>
<td>70</td>
<td>99.23</td>
</tr>
<tr>
<td>80</td>
<td>99.92</td>
</tr>
<tr>
<td>90</td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

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 $\geq$PF at Different CMPWL by Reducing Population Variability and with $C = 63$ CMPWL

<table>
<thead>
<tr>
<th>PWL</th>
<th>Prob of Receiving $\geq$PF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.1</td>
</tr>
<tr>
<td>20</td>
<td>3.93</td>
</tr>
<tr>
<td>30</td>
<td>22.43</td>
</tr>
<tr>
<td>40</td>
<td>51.02</td>
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<tr>
<td>50</td>
<td>78.44</td>
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<td>60</td>
<td>93.8</td>
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<td>70</td>
<td>99.36</td>
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<td>99.94</td>
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<tr>
<td>90</td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

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