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MULTIVARIATE VOLUMETRIC SPECIFICATIONS AND DYNAMIC MODULUS AS A QUALITY MEASURE FOR ASPHALT CONCRETE MATERIALS

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The Virginia Department of Transportation (VDOT) has worked toward end-result specifications (ERSs) in asphalt concrete since the mid-1960s. As stated by Hughes et al. (2007), true ERSs can lead to a reduction in VDOT's overall inspection force resulting in considerable savings and allow for the reallocation of inspection resources to key construction and placement processes that cannot be measured upon delivery (e.g., joint tacking and construction platform preparation). The latest efforts toward this end were conducted by Hughes et al. (2007) who suggested expanding the quality measures for asphalt concrete acceptance to include the asphalt concrete volumetric properties of voids in total mix (VTM) and voids in mineral aggregates (VMA), along with the already used asphalt content (AC) and gradation. This report builds on that and further investigates, through the use of the asphalt concrete dynamic modulus, how performance-related ERSs can be introduced into a quality assurance (QA) plan. Specifically, the report 1) documents the current variability of VTM, VMA, and AC; 2) explores different QA specification plans; and 3) develops and applies a method to predict asphalt concrete rutting performance from asphalt concrete dynamic modulus test results using the mechanistic-empirical pavement design guide (MEPDG).

Contractor volumetric test results (for the years 2006 through 2008) for VTM, VMA, and AC were obtained from VDOT's central database for production asphalt concrete. Statistical measures of mean, variance and covariance were calculated. The experimental distribution of test results for each of the three volumetric measures was obtained and compared to the normal (Gaussian) distribution. This research used these data and exploratory analysis to present alternative QA plans, which ranged from a simple univariate plan to a multivariate percent within limits (PWL) plan. The choice of a specific plan to implement depends, among other criteria, on the variable—more specifically on the correlation between these variables—that are included as part of this plan. The PWL method for "uncorrelated" variables (in this case VTM and AC) is recommended as it presents a sound statistical approach that avoids the complexities that result from incorporating correlated variables.

With advances in mechanistic-empirical pavement design methods (specifically the new MEPDG), a framework for performance-related ERSs is now available. The dynamic modulus as a function of temperature and frequency is the main asphalt concrete material input property in the MEPDG. It has significant influence on distress prediction, which makes it a quality candidate test for performance-related ERSs. A principal technical barrier to using the dynamic modulus test is the time required to perform the test temperature sweep. To address this obstacle, this report presents a method to reduce the required number of tests to characterize asphalt concrete rutting characteristics. It demonstrates that a single dynamic modulus test is sufficient to estimate asphalt concrete rutting potential as calculated by the MEPDG. This is an initial step towards using the dynamic modulus in performance-related ERSs. However, actual implementation still depends on broader acceptance and use of the dynamic modulus testing equipment and procedures, as well as the proper calibration of the MEPDG distress models to reflect observed field performance. If and when this is accomplished, the method can be extended to fatigue cracking.

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ABSTRACT

The Virginia Department of Transportation (VDOT) has worked toward end-result specifications (ERSs) in asphalt concrete since the mid-1960s. As stated by Hughes et al. (2007), true ERSs can lead to a reduction in VDOT's overall inspection force resulting in considerable savings and allow for the reallocation of inspection resources to key construction and placement processes that cannot be measured upon delivery (e.g., joint tacking and construction platform preparation). The latest efforts toward this end were conducted by Hughes et al. (2007) who suggested expanding the quality measures for asphalt concrete acceptance to include the asphalt concrete volumetric properties of voids in total mix (VTM) and voids in mineral aggregates (VMA), along with the already used asphalt content (AC) and gradation. This report builds on that and further investigates, through the use of the asphalt concrete dynamic modulus, how performance-related ERSs can be introduced into a quality assurance (QA) plan. Specifically, the report 1) documents the current variability of VTM, VMA, and AC; 2) explores different QA specification plans; and 3) develops and applies a method to predict asphalt concrete rutting performance from asphalt concrete dynamic modulus test results using the mechanistic-empirical pavement design guide (MEPDG).

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INTRODUCTION

The Virginia Department of Transportation (VDOT) has worked toward end-result specifications (ERSs) in asphalt concrete since the mid-1960s. The latest efforts toward this end were conducted by Hughes et al. (2007) who suggested expanding the quality measures for asphalt concrete acceptance to include the asphalt concrete volumetric properties of voids in total mix (VTM) and voids in mineral aggregates (VMA) along with the already used asphalt content (AC) and gradation. For asphalt concrete pavement acceptance, the authors suggested the use of field density and ride quality (smoothness) with permeability as a secondary quality check. The statistical quality measure suggested for use is the percent within limits (PWL) procedure stipulated by the American Association of State Highway and Transportation Officials (AASHTO) in R-009-05, Standard Recommended Practice for Acceptance Sampling Plans for Highway Construction, and R042-06, Recommended Practice to Develop a Quality Assurance Plan for Hot-Mix Asphalt. This method differs from the current provision by combining the average and standard deviation into a single measure, which is the PWL.

For the effective application of any quality acceptance plan, including the PWL, “appropriate” process limits should be used. What is meant by “appropriate” is that these limits should work for both the contractor and the specifying agency; therefore, these limits should be achievable by the contractor within reasonable effort. Perhaps the best source of information that can guide the development of process limits is the one obtained from historical information about process accuracy and variability (i.e., what are we achieving right now?). VDOT has a wealth of data on the production of asphalt concrete mixtures. The data are stored in a database that contains aggregate gradations, AC and volumetrics (VTM and VMA) for designed and produced material. While available, these data had not been analyzed statistically to evaluate variability during production. Hughes et al. (2007) found that some previously proposed limits were not appropriate; the analysis of VDOT's database can help redefine these limits.

The best ERS would use quality characteristics through which the performance of the constructed pavement (or pavement element) can be predicted. While in the past performance prediction has been a difficult task, the new mechanistic-empirical pavement design guide (MEPDG) that resulted from the National Cooperative Highway Research Program (NCHRP) Project 1-37A presents a viable solution. With appropriate calibration, the MEPDG can potentially provide a tool for pavement performance prediction. The drawbacks of using the MEPDG for this purpose are the large number of input variables needed and the relatively long time required to run the MEPDG software. To address these drawbacks, Witczak of Arizona State University suggested developing performance prediction equations based on specific pre-solved inputs to the MEPDG. Given acceptable accuracy of these equations, they can be used as a simpler and faster alternative to the MEPDG to predict pavement performance.

PURPOSE AND SCOPE

The purpose of this study was to continue the move toward ERSs for asphalt concrete materials and construction by building on the latest results from Hughes et al. (2007). The study also extends the efforts toward performance-related ERSs using the dynamic modulus to align with national initiatives to apply the concepts of mechanistic-empirical analysis and design. The scope of this study was:

- Analyze historical data from asphalt concrete production to help develop realistic specification limits. These include volumetric data such as VTM, liquid asphalt AC, and VMA.
- Use the analysis of historical data to evaluate different acceptance plans that can combine multiple quality measures for implementation as ERSs.
- Evaluate the potential use of the dynamic modulus as a quality measure for rutting of asphalt concrete mixes.

METHODS

Contractor Volumetric Data Analysis

VDOT's central database was queried for contractor test results of the AC, VTM, and VMA. Average, variance, correlation, and normality assumptions were evaluated for 2006 through 2008. Process variation is relevant to setting specification limits of an acceptance plan while data normality is an important characteristic as it is an assumption made in most acceptance plans.

Evaluate Different Acceptance Plans

A total of five acceptance plans with different levels of complexity were investigated. These included (1) a simple plan that combines average and standard deviation, (2) a PWL approach for a single variable using the minimum variance unbiased (MVU) estimator, (3) a PWL approach for a single variable using the maximum likelihood (ML) estimator, (4) a multivariable PWL approach using the MVU estimator, and (5) a multivariable PWL approach using the ML estimator.

Mix Rutting Performance Prediction from Dynamic Modulus

The final task sought to develop a procedure that uses the dynamic modulus as a quality measure for rutting potential of asphalt concrete mixes. This procedure was conducted to reflect the current efforts to evaluate the dynamic modulus as a performance-related quality measure as part of NCHRP Project 9-22 and NCHRP Project 9-30A, both of which are expected to be completed in 2010. The MEPDG was used to evaluate the rutting potential of the mixes. To reduce the number of tests, an effective reduced frequency (defined as the reduced frequency at which the dynamic modulus best correlates with the asphalt concrete rutting) was determined and calculated using the MEPDG. This would significantly reduce testing time, thereby making the test better suited for an acceptance plan. Samples collected from three different resurfacing projects were used to evaluate and illustrate the procedure.

RESULTS AND DISCUSSION

VTM, AC, and VMA Process Variability

Analysis of historical volumetric properties can give valuable information to help develop specification limits for a quality assurance (QA) acceptance plan. The analysis performed identified the current process variation and the correlation between the different variables. Process variation is essential in determining realistic specification limits, while correlation between the different variables will affect the choice of an analysis method. The volumetric properties used are the VTM, AC, and VMA. The statistical parameters investigated are process mean, variance (or standard deviation), normality assumptions, and correlation between the variables (VTM, AC, and VMA).

Voids in Total Mix (VTM)

The VTM is defined as the percentage by volume of air voids in the mix. The VTM is the primary design parameter in the Superpave mix design procedure where a target VTM (generally 4%) is set at a certain number of design gyrations (using the Superpave gyratory compactor). This target VTM is achieved by adjusting the AC. The VTM affects the mix performance and ultimately the pavement performance in terms of distress development.

VTM Process Mean and Variance

Figure 1 shows the laboratory measured VTM for all mixes used during the 2006, 2007, and 2008 paving seasons versus the target VTM as reported in the job-mix formula (JMF) sheet. Mixes were combined after a preliminary analysis of the VTM revealed statistical measures (mean and standard deviation) did not depend on the mix type (BM, IM, SM, and SMA). Figure 1 is based on more than 10,000 observations included in VDOT's central database. No data subdivision into project, district, or asphalt plant was undertaken. VDOT requires mixes to be designed for a VTM of 4% according to Superpave. However, the approved JMF VTM is not always 4%. After inquiring with the Districts Materials Divisions it was found that deviations from the 4% target VTM can be due to two main reasons: (1) when trial batches achieve a VTM close to 4% (e.g., 3.8% to 4.2%), this percentage will be approved by the district as it is deemed "close enough" to 4% for all practical reasons; and (2) sometimes, based on experience, districts will approve a VTM different than 4% (e.g., 3%) knowing this is the required laboratory VTM the contractor has to use to achieve appropriate field compaction. For a target VTM greater than 3%, the average laboratory VTM was lower than the target VTM (calculated average falls under the line of equality). The difference increased with an increasing target VTM. Not enough test data are available to make a definitive conclusion below a 3% design VTM, although it seems the measured VTM is greater than the target VTM.

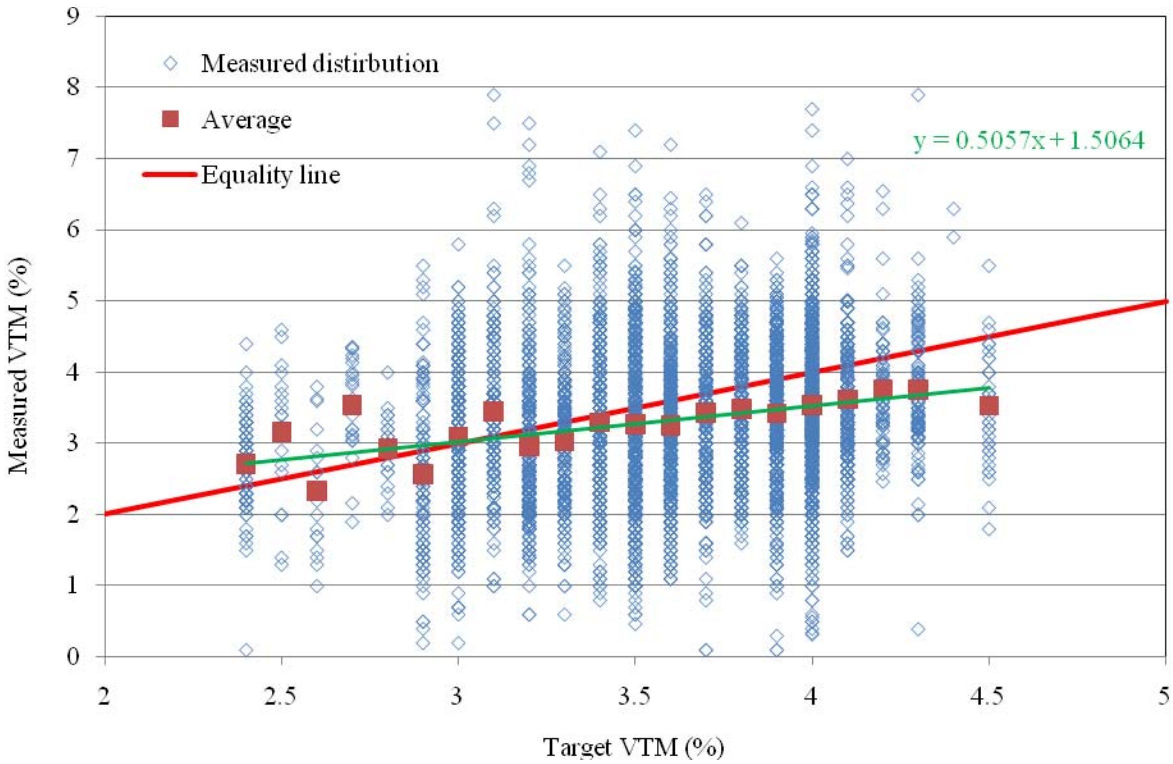

Figure 1. Measured VTM vs. target VTM.

The standard deviations at each target VTM are presented in Figure 2. The standard deviations varied between 0.49 and 1.11%. These two extrema are for a target VTM of 2.8 and 2.9% and are based on 21 and 126 measurements, respectively, and therefore cannot be considered very representative of the actual population standard deviation. Most VTM measurements were taken for a target VTM between 3.5 and 4.0% for which the standard deviation varied between 0.78 and 0.89%. Bartlett's test for equal VTM variance (square of the standard deviation) was performed on measurements taken for a target VTM between 3.5 and 4.0%. The test result rejected the hypothesis that the variances at different target VTMs are equal. Although statistical analysis rejected the assumption of equal variances, the difference between 0.78 and 0.89% is relatively small from a practical engineering perspective so that a pooled standard deviation would be appropriate to characterize the process variation. The pooled standard deviation was calculated as 0.86% using Equation 1.

$$S_p = \sqrt{\frac{\sum_{i=1}^{k}\left((n_i-1)s_i^2\right)}{\sum_{i=1}^{k}(n_i-1)}} \qquad \text{(Eq. 1)}$$

where

S_p = pooled standard deviation
S_i = standard deviation at a specific VTM
n_i = number of samples at a specific VTM

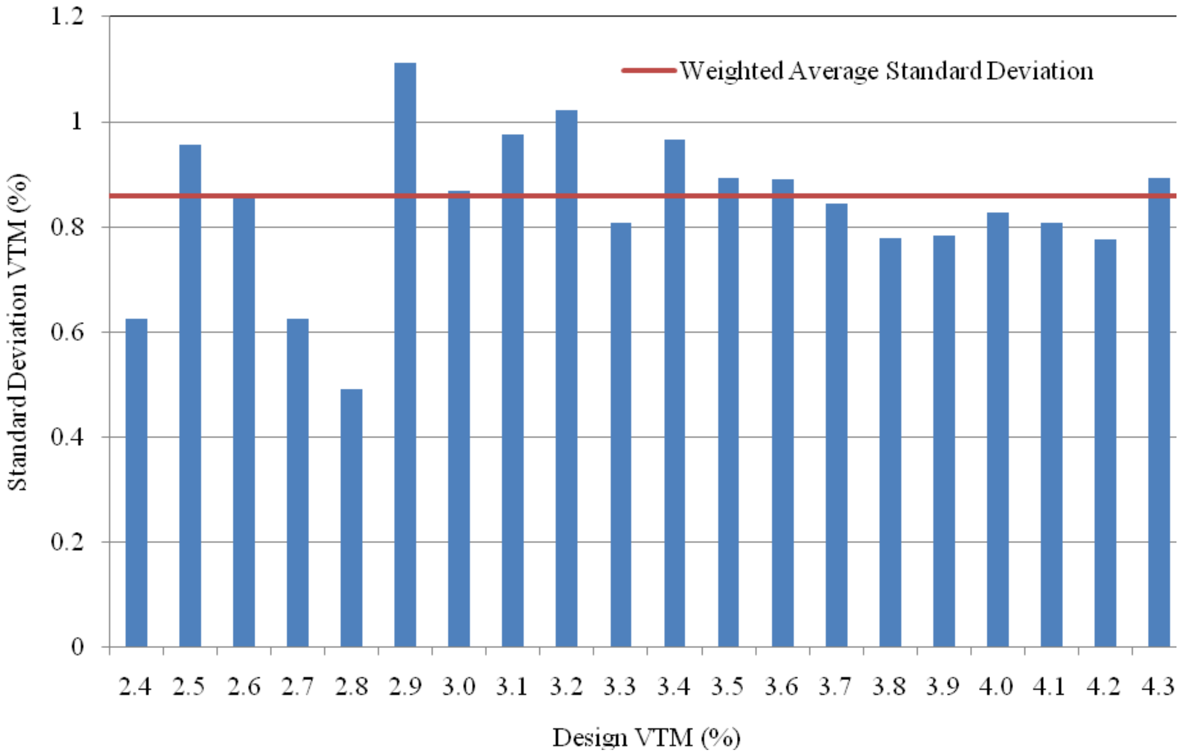

Figure 2. VTM standard deviation.

Normality Test

Normality of the process is important due to the fact that most statistical data analysis methods such as the PWL were developed under the assumptions of normality. Deviations from normality can cause statistical measures to be incorrectly calculated. For example, Burati and

Weed (2006) investigated the effect of deviation from normality on the calculation of the PWL by simulating distribution with different skewnesses. Figure 3 shows the VTM cumulative distribution for a target VTM of 4% for all mixes (BM, IM, SM, and SMA). Graphically, the figure suggests that the measured VTM follows more or less a normal distribution with an average of 3.5%, which is less than the target 4%. However, the distribution failed Pearson's Chi-square test, D'Agostino's K-squared test, and the Anderson-Darling test for normality. Deviations from normality are more easily observed when the VTM histogram shown in Figure 4 is compared to the normal distribution with average and standard deviation calculated from the experimental data. Figure 4 suggests there are two peaks at approximately 3.5% and 4.6%. Further analysis showed that these two peaks are also observed when the data are analyzed according to the mix type (BM, IM, SM, and SMA) and therefore cannot be attributed to different mixes having a different average VTM. To illustrate the two peaks, a binormal (sum of two normal distributions) distribution was fit to the data as shown in Figure 4. The binormal distribution is defined according to Equation 2.

$$B_{\alpha,\mu_1,\mu_2,\sigma_1,\sigma_2}(x) = \alpha N_{\mu_1,\sigma_1}(x) + (1-\alpha) N_{\mu_2,\sigma_2}(x) \qquad \text{(Eq. 2)}$$

where

$B_{\alpha,\mu_1,\mu_2,\sigma_1,\sigma_2}$ = binormal distribution
N_{μ_1,σ_1} and N_{μ_2,σ_2} = normal distribution with different parameters
μ = mean of the normal distribution
σ = standard deviation of the normal distribution
α = parameter between 0.5 and 1

The parameters α, μ_1,μ_2,σ_1,and σ_2 are determined to provide the best fit to the experimental data. For the case of a 4% target VTM, α was calculated as 0.96, and μ_1, μ_2, σ_1, and σ_2 were calculated as 3.50%, 4.73%, 0.78%, and 0.15%, respectively. This suggests most of the data (96%) comes from a single normal distribution while deviations from normality are due to 4% of the experimental data. Causes for the deviations from normality are not easily determined; however, possible causes can be attributed to a specific production plant or a specific production period where, for some reason, the process had different characteristics.

The skewness calculated for the data consisting of a 4% target VTM was 0.1 (note that skewness is independent of the magnitude of the test data). Based on the results presented by Burati and Weed, this number is likely too low to appreciably affect the calculations of the PWL compared to the case where the data are normally distributed.

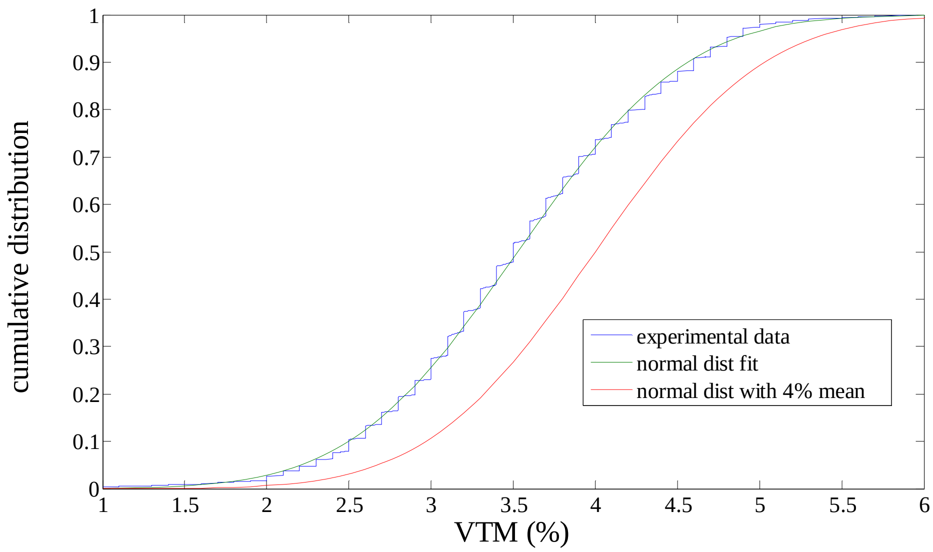

Figure 3. Cumulative VTM distribution for design VTM of 4%.

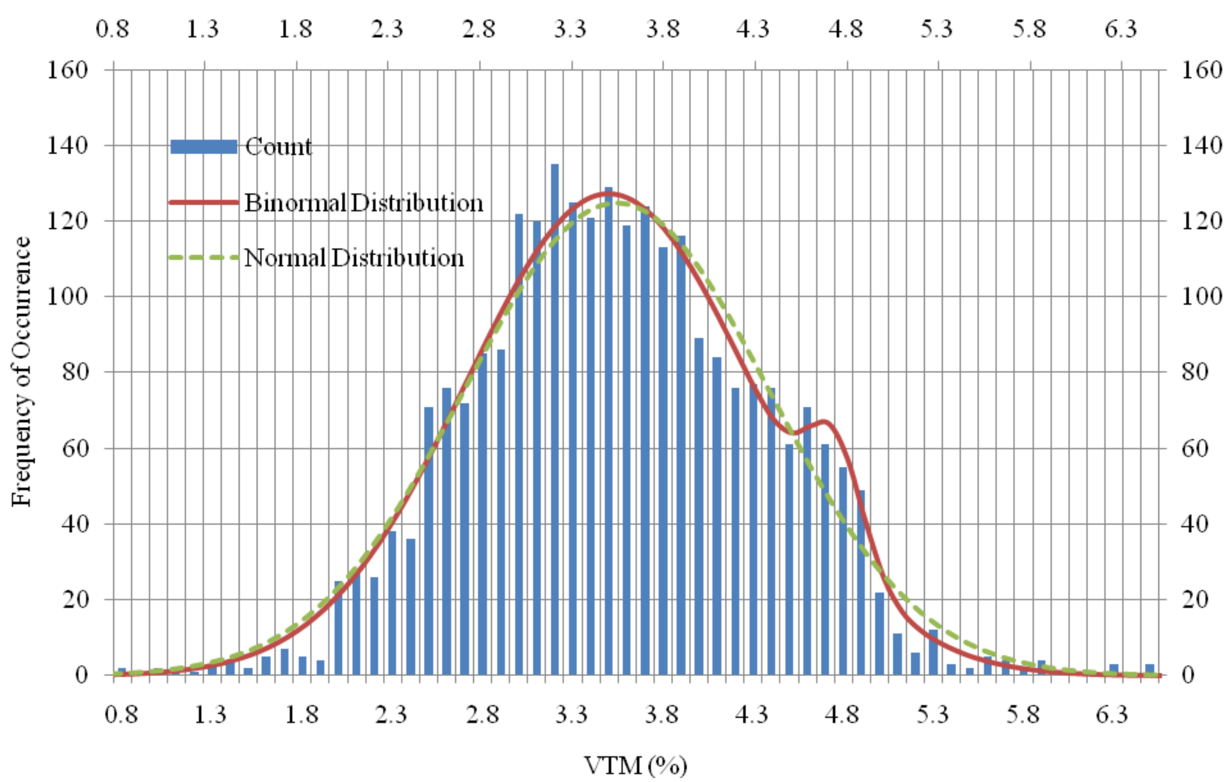

Figure 4. VTM histogram for 4% target VTM.

Confidence Intervals for the Mean and Standard Deviation

Confidence intervals for the process mean and standard deviation for different sample sizes were determined assuming the VTM standard deviation is equal to 0.86% (pooled standard deviation). This was chosen as it represents a realistic achievable process variation as evidenced from the analysis of the VTM data. From the central limit theorem, averages calculated from data sampled from any statistical distribution tend to be normally distributed with the standard deviation calculated according to Equation 3.

$$\sigma_\mu = \frac{\sigma}{\sqrt{n}} \qquad \text{(Eq. 3)}$$

where

σ	=	population standard deviation (0.86%)
σ_μ	=	standard deviation of mean response of n samples
n	=	number of samples

From the standard deviation, confidence intervals for the mean response can be obtained for different confidence levels as presented in Table 1. These can be interpreted as such for the case of a sample size of three samples: 99% of the time, the calculated mean will fall within 1.29% distance from the actual mean response (assuming the process standard deviation is equal to 0.86%). Therefore, calculated mean values that are more than 1.29% away from the design process mean (for example, 4%) are very unlikely (occurs 1% of the time) so that it can be assumed that the actual achieved mean is different from 4%.

Table 1. VTM confidence interval of mean response for different sample sizes

Sample Size	**Confidence Interval for Different Percentages**											
	99	**95**	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**	**5**
3	1.29	0.98	0.82	0.64	0.52	0.42	0.34	0.26	0.19	0.13	0.06	0.03
4	1.11	0.84	0.71	0.55	0.45	0.36	0.29	0.23	0.17	0.11	0.05	0.03
5	0.98	0.74	0.63	0.49	0.39	0.32	0.26	0.20	0.15	0.10	0.05	0.02
6	0.90	0.69	0.58	0.45	0.36	0.29	0.24	0.18	0.13	0.09	0.04	0.02
7	0.85	0.65	0.54	0.42	0.34	0.28	0.22	0.17	0.13	0.08	0.04	0.02
8	0.77	0.59	0.49	0.38	0.31	0.25	0.20	0.16	0.12	0.08	0.04	0.02
9	0.75	0.57	0.48	0.37	0.30	0.24	0.20	0.15	0.11	0.07	0.04	0.02
10	0.70	0.53	0.44	0.35	0.28	0.23	0.18	0.14	0.10	0.07	0.03	0.02
12	0.64	0.49	0.41	0.32	0.26	0.21	0.17	0.13	0.10	0.06	0.03	0.02
15	0.57	0.43	0.36	0.28	0.23	0.19	0.15	0.12	0.08	0.06	0.03	0.01
20	0.49	0.37	0.31	0.24	0.20	0.16	0.13	0.10	0.07	0.05	0.02	0.01
30	0.41	0.31	0.26	0.21	0.17	0.13	0.11	0.08	0.06	0.04	0.02	0.01
40	0.36	0.27	0.23	0.18	0.15	0.12	0.09	0.07	0.05	0.04	0.02	0.01
50	0.31	0.24	0.20	0.15	0.12	0.10	0.08	0.06	0.05	0.03	0.02	0.01
100	0.23	0.18	0.15	0.12	0.09	0.08	0.06	0.05	0.03	0.02	0.01	0.01

Table 2. VTM confidence interval for the standard deviation for different sample sizes

Sample Size	Confidence Interval for Different Percentages											
	99	**95**	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**	**5**
3	1.85	1.49	1.30	1.09	0.94	0.82	0.72	0.61	0.51	0.41	0.28	0.19
4	1.67	1.39	1.24	1.07	0.95	0.85	0.76	0.68	0.59	0.50	0.38	0.29
5	1.57	1.32	1.20	1.05	0.95	0.86	0.79	0.71	0.64	0.55	0.44	0.36
6	1.49	1.28	1.17	1.04	0.95	0.87	0.80	0.74	0.67	0.59	0.49	0.41
7	1.44	1.25	1.15	1.03	0.94	0.87	0.81	0.75	0.69	0.62	0.52	0.45
8	1.40	1.22	1.13	1.02	0.94	0.88	0.82	0.76	0.70	0.64	0.55	0.48
9	1.36	1.20	1.11	1.01	0.94	0.88	0.82	0.77	0.71	0.65	0.57	0.50
10	1.33	1.18	1.10	1.00	0.94	0.88	0.83	0.78	0.72	0.66	0.59	0.52
12	1.29	1.15	1.08	0.99	0.93	0.88	0.83	0.79	0.74	0.69	0.61	0.55
15	1.24	1.12	1.05	0.98	0.93	0.88	0.84	0.80	0.76	0.71	0.64	0.59
20	1.19	1.08	1.03	0.96	0.92	0.88	0.84	0.81	0.77	0.73	0.67	0.63
30	1.12	1.04	1.00	0.95	0.91	0.88	0.85	0.82	0.79	0.76	0.71	0.67
40	1.09	1.02	0.98	0.94	0.90	0.88	0.85	0.83	0.80	0.77	0.73	0.70
50	1.06	1.00	0.97	0.93	0.90	0.88	0.85	0.83	0.81	0.78	0.75	0.72
100	1.00	0.96	0.94	0.91	0.89	0.87	0.86	0.84	0.83	0.81	0.78	0.76

Unlike the confidence intervals for the mean response, confidence intervals on the standard deviation are based on the assumption that the data are normally distributed. In this case, the sample variance follows a chi-square distribution (Equation 4).

$$(n-1)\frac{s^2}{\sigma^2} \sim \chi^2_{n-1} \qquad \text{(Eq. 4)}$$

The confidence intervals for the process standard deviation for different sample sizes are presented in Table 2. These intervals extend from zero to the value reported in the table. These can be interpreted as such for the case of a sample size of three samples: 99% of the time, the calculated standard deviation will be less than 1.85% (assuming the process standard deviation is equal to 0.86%).

Asphalt Content (AC)

The AC is defined as the percentage by weight of asphalt binder in the mix. In the Superpave mix design procedure, the AC is adjusted to achieve the target VTM. To determine process variability, the AC content was analyzed for all mixes (SM, BM/IM, and SMA). The AC distribution (histogram) for 2008 is presented in Figure 5. Initial analysis of the data showed they were not normally distributed; rather it revealed two prominent peaks at approximately 4.4% and 5.4% and a less prominent peak at 6.4%. Further analysis of the data showed these peaks corresponded to the average AC for the BM and IM, SM, and SMA, respectively. Further analysis of each mix type showed that the data were normally distributed (Figure 5) according to D'Agostino's K-squared test for normality; however, it fails Pearson's Chi-square test and the Anderson-Darling test. The mean and standard deviation for each mix type (BM/IM, SM, and

SMA) are presented in Table 3. As expected, coarser mixes required less AC while the SMA required the most AC.

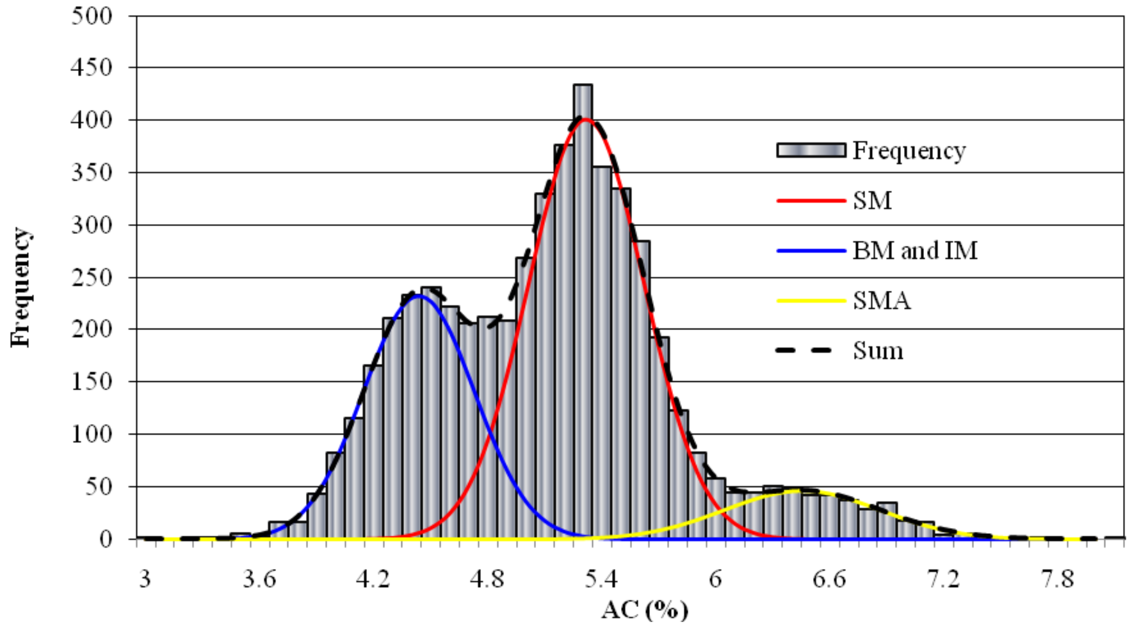

Figure 5. AC distribution (2008)

Table 3. Mean and standard deviation measures of AC for all mixes

Year	BM/IM		SM		SMA	
	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Deviation
2008	4.44	0.29	5.32	0.30	6.45	0.41
2007	4.33	0.25	5.24	0.32	6.39	0.45
2006	4.34	0.28	5.28	0.32	6.22	0.45

Confidence Intervals on Mean and Standard Deviation

Confidence intervals for the AC process mean and standard deviation for different sample sizes were determined assuming the AC standard deviation, which is equal to 0.3%. The 0.3% was chosen as a compromise reflecting the standard deviation of the SM and BM/IM mixes. The SMA was not considered because of the relatively small percentage of SMA used in paving projects (less than 10%). The confidence intervals for the process mean and process standard deviation for the AC are presented in Appendix A.

Correlation Between the VTM and AC

Correlation among acceptance measures determines what acceptance sampling plan to use. High correlation among acceptance measures requires acceptance plans that take the correlation into account, while low correlation can be ignored as it does not sensibly affect the results. How to handle multivariate acceptance using the PWL for the correlated and uncorrelated cases is illustrated later in the report.

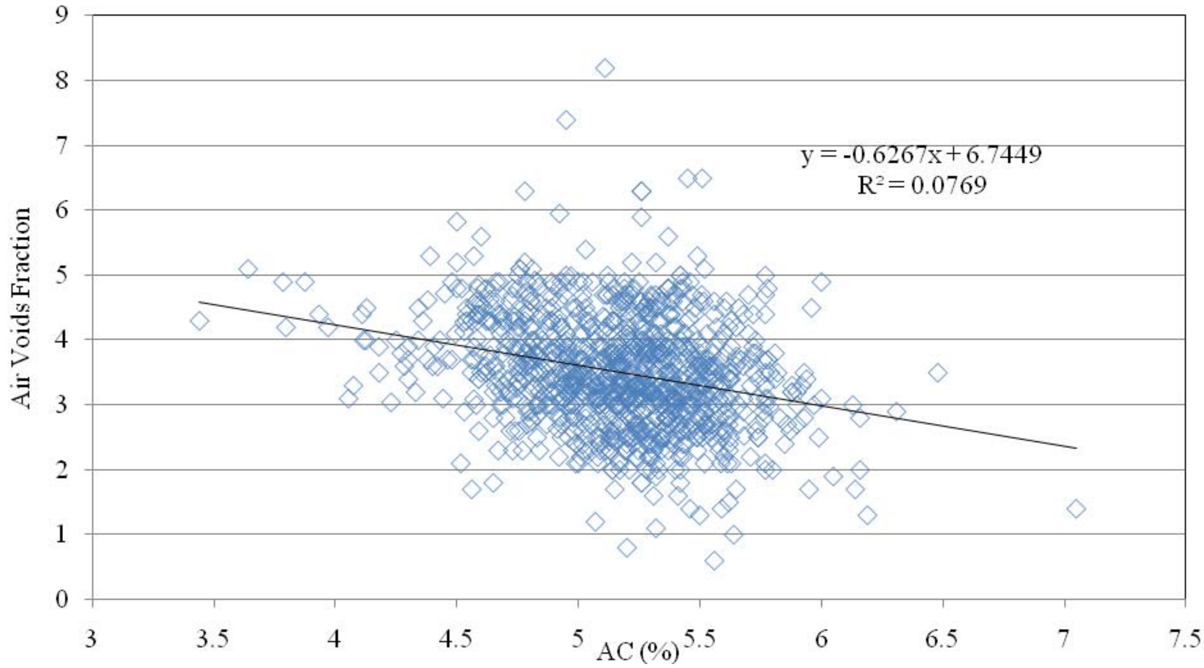

Figure 6. VTM-AC plot for SM mixes and 4% target air voids

A plot of the VTM versus the AC is presented in Figure 6. The general trend shows a decrease in the VTM with increase in the AC. This is expected as an excess binder added to the mix fills the available air voids. Although there is a general trend relating the VTM to the AC, the calculated correlation of -0.28 (the negative sign is because an increase in one variable results in a decrease in the other) between the two variables is not very high, and much of the variation in one of the two variables is independent of the other.

Voids in Mineral Aggregates

The VMA was suggested to be included in a quality acceptance plan by Hughes et al. (2007) as it is already measured by VDOT. The average VMA for all mixes from 2006 to 2008 are presented in Table 4. These fall within VDOT specifications (VDOT, 2007). The differences between the means are all statistically significant. The BM had the lowest average VMA values while the SMA had the highest average VMA values. The VMA distribution for SM9.5 mixes is presented in Figure 7. This distribution failed all three tests of normality. Two theoretical distributions are plotted to illustrate the deviations from normality. The first distribution is the normal distribution with the average and standard deviation taken from Table 4 (16.15% and 0.92%). The second distribution is the skew normal distribution, which provides a better representation of the experimental data. The standard skew normal distribution is defined as:

$$f(x) = 2\phi(x)\Phi(\alpha x) \tag{5}$$

where

$f(x)$ = standard skew normal distribution

$2\phi(x)$ = standard normal distribution
$\Phi(x)$ = standard cumulative normal distribution
α = shape parameter related to skewness (for α = 0, the standard normal distribution is recovered)

The skew normal distribution is provided to illustrate the experimental data's deviation from normality. Note that although the skew normal distribution provides a better representation of the experimental data, it still fails Pearson's goodness of fit test (though not as "poorly" as the normal distribution).

Table 4. Mean, standard deviation, and skewness measures for the VMA

Mix	Average (%)	Standard Deviation (%)	Skew
SM9.5	16.15	0.92	0.479
SM12.5	15.61	0.88	0.613
BM	13.84	1.00	-0.005
SMA	18.18	1.09	0.615

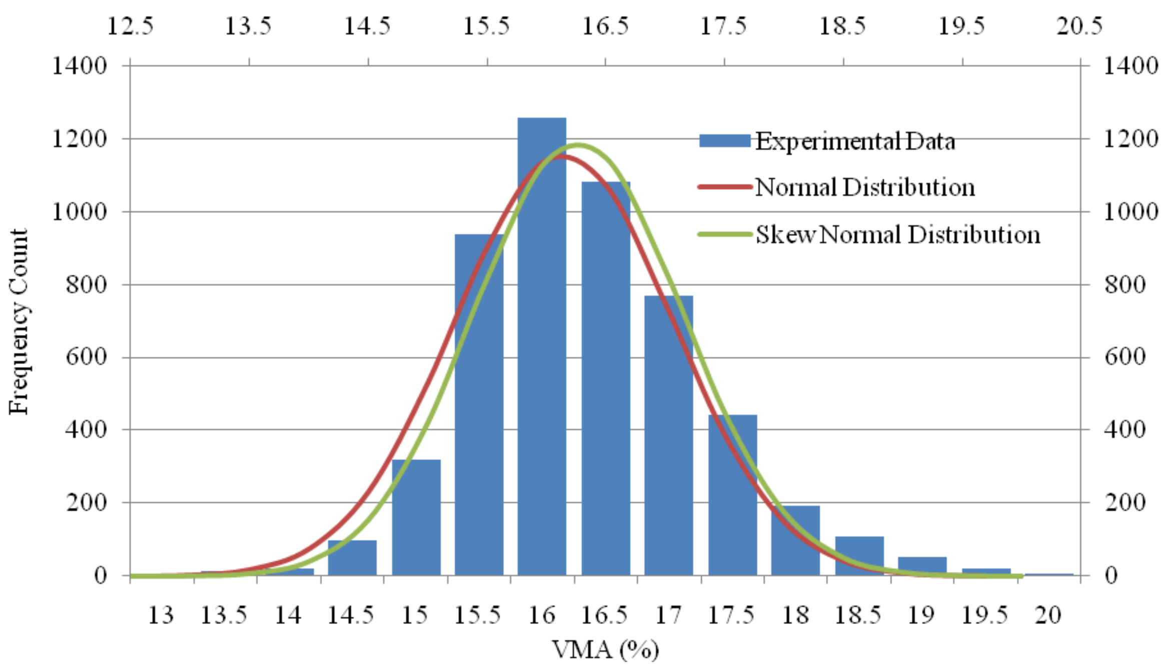

Figure 7. Measured VMA for SM9.5

Confidence Intervals on Mean and Standard Deviation

Similar to the case for the VTM and AC, confidence intervals on the process mean and standard deviation for the VMA for different sample numbers were determined assuming the VMA standard deviation is equal to 1.0% (based on results from Table 4). The 1.0% was chosen as a single value compromise for all mix types. The results of process mean and process standard deviation for the VMA are presented in Appendix A.

Correlation Between the VMA, VTM, and AC

Correlation between the different performance measures should be considered for proper statistical evaluation. Failure to recognize this may lead to erroneous results, especially when the correlation is high. The correlation between the VTM, VMA, and AC is presented in Table 5. Table 5 shows that, to some degree, all three measures are correlated. The largest correlation is between the VTM and VMA (around 0.65) followed by the VMA and AC (around 0.4) and the VTM and AC (around -0.25). Since all three measures are correlated, the partial correlation between the VTM and VMA with the effect of the AC removed (Equation 6) was calculated with results ranging between 0.81 and 0.85. This strong correlation is expected since the VMA is a measure of total volume that does not consist of the aggregate skeleton and comprises the effective binder volume and the VTM. To visualize the correlation between the VMA as the dependent variable and the VTM and AC as the independent variables, a multiple linear regression was performed. The results are presented in Figure 8 where the VMA calculated from the regression model (regressed VMA) is plotted against the measured VMA. This shows that the VMA can be fairly well estimated from the VTM and AC.

$$\rho_{VTM.VMA/AC} = \frac{\rho_{VTM.VMA} - \rho_{VTM.AC}\rho_{VMA.AC}}{\sqrt{1-\rho^2_{VTM.AC}}\sqrt{1-\rho^2_{VMA.AC}}} \quad \text{(Eq. 6)}$$

where

$\rho_{VTM.VMA/AC}$ = partial correlation between the VTM and VMA with the effect of the AC removed

$\rho_{VTM.VMA}$ = correlation between the VTM and VMA

$\rho_{VTM.AC}$ = correlation between the VTM and AC

$\rho_{VMA.AC}$ = correlation between the VMA and AC

Table 5. Correlation between the VTM, AC, and VMA

Mix	**Correlation**			
	VTM/VMA	**VTM/AC**	**VMA/AC**	**VTM/VMA.AC**
SM9.5	0.66	-0.23	0.38	0.83
SM12.5	0.58	-0.33	0.43	0.85
BM	0.63	-0.22	0.45	0.84
SMA	0.68	-0.25	0.27	0.81

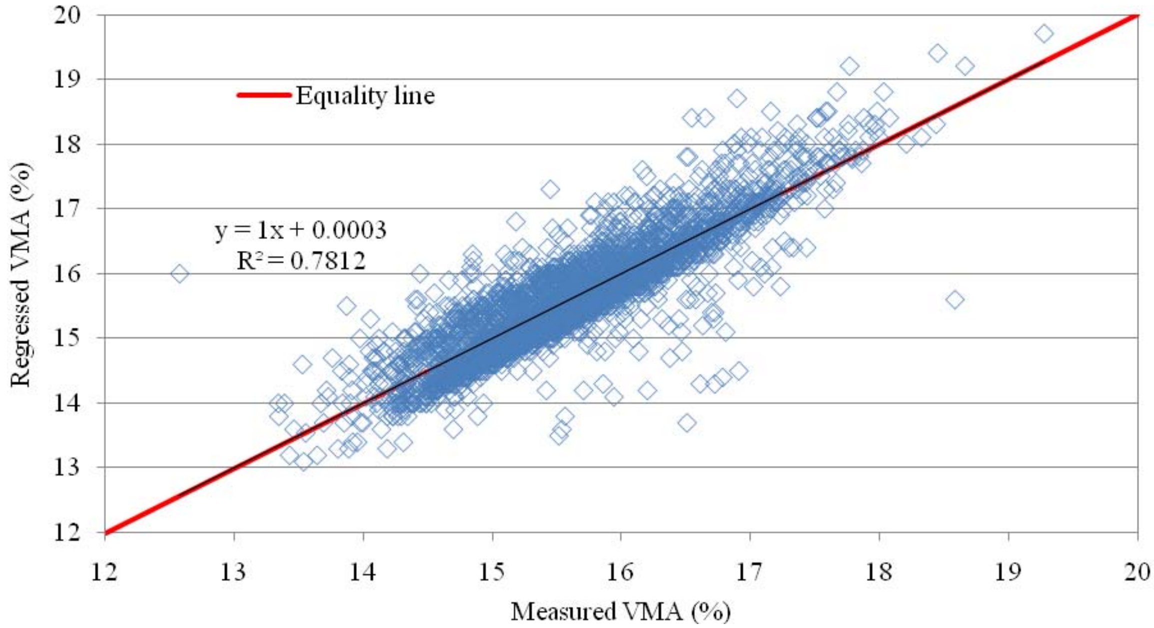

Figure 8. Comparison between predicted VMA and measured VMA

QA Acceptance Plans

Different acceptance sampling plans are presented in this section. These plans range from the simple plan that considers each quality measure (i.e., the VTM, AC, and VMA) separately without considering data correlation and by using a simple empirical method of combining the process mean and variation (standard deviation) to the fully three-dimensional PWL procedure that takes into account the correlation between the three quality measures. Some of the advantages and disadvantages of each method are also pointed out.

Simple Plan Combining Averages and Standard Deviations

The main advantage of this acceptance plan is its simplicity in combining the process average and standard deviation, making it easier to implement than the PWL procedure. The main disadvantage of the plan is that it combines average and standard deviation in an empirical way. The procedure presented here is based on the developed confidence intervals for each quality measure. Since these confidence intervals were established based on historical data during a three-year period, they are assumed to reflect the current level of control contractors are achieving. Measured averages and standard deviations that fall within smaller confidence intervals suggest better process control than values that fall within larger intervals. For example, a sample calculated average that falls outside the 95% confidence interval suggests (with a high probability) that the actual population average is different than the target average. On the other hand, a sample calculated average that falls within the 5% confidence interval suggests (with high probability) that the actual population average is very close to the target average. A similar argument can be made for the process standard deviation. In other words, values that fall within smaller confidence intervals for both the average and standard deviation are the "best," while values that fall outside large confidence intervals for both average and standard deviation are the "worse" in terms of achieving the target value with high accuracy. This idea can be visually illustrated in a matrix as shown in Table 6. Table 6 shows a division of the acceptance-rejection regions based on where the calculated average and standard deviation fall within the different confidence intervals. The subdivisions presented here are for illustration, and a final subdivision would be determined based on more information from actual projects. Also note that in this matrix, equal weights are given to the process mean and standard deviation; this does not have to be the case. Another possible way of combining the process mean and standard deviation is to determine a weighted arithmetic mean or a weighted geometric mean of the confidence interval for the processes. The weighted arithmetic mean and weighted geometric mean are determined according to Equations 7 and 8, respectively.

$$\bar{p} = \frac{w_{mean}p_{mean} + w_{std}p_{std}}{w_{mean} + w_{std}} \qquad \text{(Eq. 7)}$$

$$\bar{p} = [(w_{mean}p_{mean})(w_{std}p_{std})]^{w_{mean}+w_{std}} \qquad \text{(Eq. 8)}$$

For the case where two or more variables are monitored, a weighted arithmetic mean or geometric mean can be used to combine the variables into one single measure.

Table 6. Matrix for proposed acceptance plan

Confidence Interval for Mean	Confidence Interval for Standard Deviation																		
	95	90	85	80	75	70	65	60	55	50	45	40	35	30	25	20	15	10	5
95	Reject	Reject	Reject	Reject	0.9	0.9	0.9	0.9	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98
90	Reject	Reject	Reject	0.9	0.9	0.9	0.9	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98
85	Reject	Reject	0.9	0.9	0.9	0.9	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98
80	Reject	0.9	0.9	0.9	0.9	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98
75	0.9	0.9	0.9	0.9	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1
70	0.9	0.9	0.9	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1
65	0.9	0.9	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1
60	0.9	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1
55	0.9	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1
50	0.9	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02
45	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02
40	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02	1.02
35	0.95	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02	1.02	1.02
30	0.95	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02	1.02	1.02	1.02
25	0.95	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02	1.02	1.02	1.02	1.05
20	0.95	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02	1.02	1.02	1.02	1.05	1.05
15	0.98	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02	1.02	1.02	1.02	1.05	1.05	1.05
10	0.98	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02	1.02	1.02	1.02	1.05	1.05	1.05	1.05
5	0.98	0.98	0.98	0.98	1	1	1	1	1	1.02	1.02	1.02	1.02	1.02	1.05	1.05	1.05	1.05	1.05

- Reject
- Pay Factor 0.9
- Pay Factor 0.95
- Pay Factor 0.98
- Pay Factor 1
- Pay Factor 1.02
- Pay Factor 1.05

PWL Procedure

Single Variable Case

The PWL procedure is well known among state departments of transportation (DOTs). Tables have been published to calculate the PWL for a single variable based on calculated average and standard deviation. In this report, a summary of the PWL procedure for single variable and multivariate acceptance sampling is presented.

The PWL method stipulated by the AASHTO was developed by Lieberman and Resnikoff (1955) as sampling plans for inspection by variables for a single normally distributed quality characteristic. Based on a collected sample from the population, the PWL is the MVU estimator of the percentage of the population that falls within the specification limits; i.e., the process conforming (PC). An unbiased estimator of a parameter is an estimator whose expected value is equal to the parameter (i.e., the average of different estimations tends to equal the parameter). A parameter can have more than one unbiased estimator, and the MVU estimator is the one that has the lowest variance among unbiased estimators (i.e., the standard deviation of different estimations is the smallest). Other estimators of the PC have been used (these are not referred to in the PWL that is known by the transportation industry) such as the ML estimator that uses the normal distribution with the ML estimates of the mean [$\bar{x} = \sum_i x_i / n$] and standard deviation [$\hat{\sigma} = \sqrt{\sum_i (x_i - \bar{x})^2 / n}$] and the slightly modified version of the ML estimator referred to as an MLS estimator, where the S stands for the unbiased estimate of the standard deviation, that uses the normal distribution with the ML estimate of the mean and the unbiased estimate of the standard deviation [$s = \sqrt{\sum_i (x_i - \bar{x})^2 / (n-1)}$] (Hamilton and Lesperance, 1995). These are biased estimators. The word biased sometimes has the stigma of being "bad," unfair, or influenced by a type of prejudice; however, this is not the case in the statistical meaning of bias of an estimator, and, in many cases, biased estimators can have more desirable properties than unbiased ones. For example, biased estimators can sometimes provide an estimate that is closer to the actual parameter, as illustrated in Figure 9. In this case there is a given parameter whose real value is 0. Two methods of estimating this parameter give rise to the two normal distributions presented in the figure. The unbiased method of estimation is the one whose mean is equal to the parameter value of 0, while the biased method of estimation has a mean different than the parameter value of 0 (in this case the mean of the biased estimation is 0.2). Clearly in this example, the biased estimation is much more accurate than the unbiased one as any single estimation has a much higher probability of being closer to the actual parameter value than the case for the unbiased estimation method.

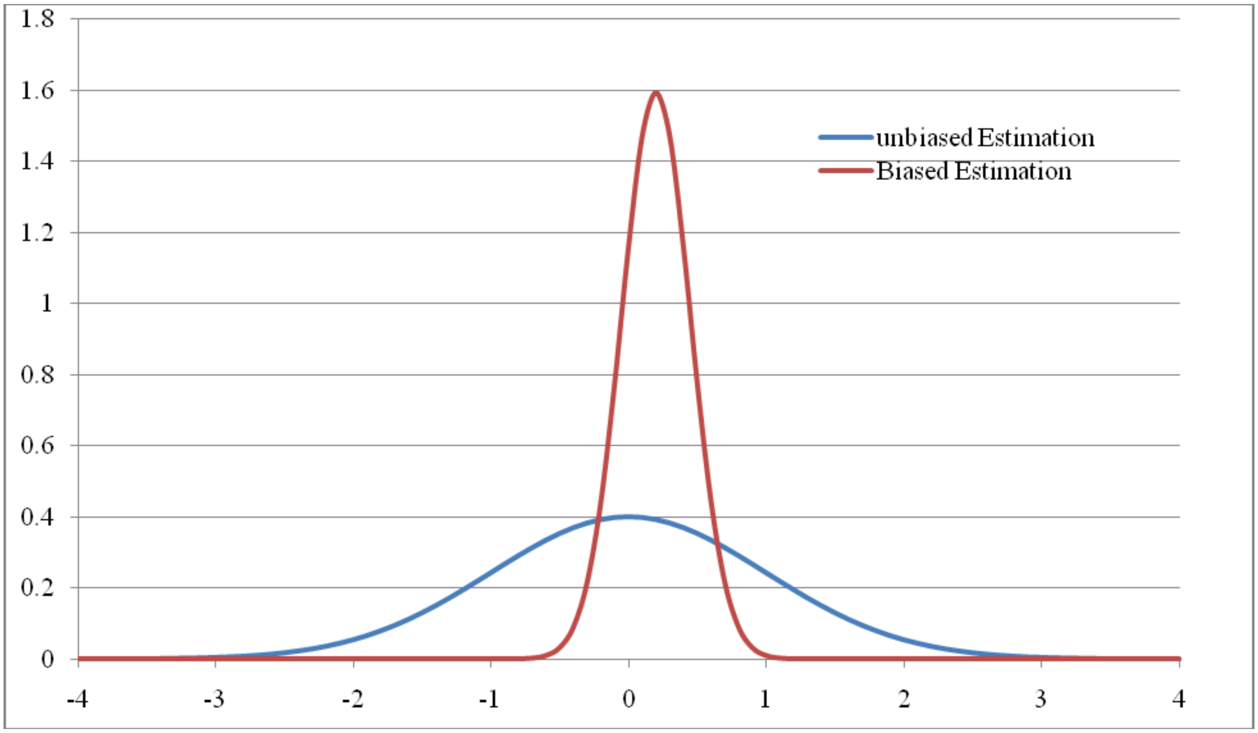

Figure 9. Illustration of biased and unbiased estimation methods

The MVU PWL (the one stipulated by the AASHTO) is calculated according to Equation 9.

$$PWL = 100\left\{1 - \left(\int_0^U beta(X, n/2-1)dX + \int_0^L beta(X, n/2-1)dX\right)\right\} \qquad \text{(Eq. 9)}$$

where

$PWL =$% within limits (MVU estimator of% conforming)
$U = \max\left[0; \frac{1}{2} - \frac{1}{2} Q_U \frac{\sqrt{n}}{n-1}\right]; \quad Q_U = \frac{L_U - \bar{x}}{s}$
$L = \max\left[0; \frac{1}{2} - \frac{1}{2} Q_L \frac{\sqrt{n}}{n-1}\right]; \quad Q_L = \frac{\bar{x} - L_L}{s}$
$beta(X, n/2-1) =$ beta probability density distribution with $\alpha = \beta = n/2 - 1$

The ML and the MLS PWL are calculated according to Equation 10.

$$P_{ML} = 100\int_{Q_L^*}^{Q_U^*} \phi(0,1)dx \qquad \text{(Eq. 10)}$$

where

$P_{ML} =$ ML estimator of% conforming
$\phi(0,1) =$ standard normal probability density function
$Q_U^* = \frac{L_U - \bar{x}}{s}$ for MLS and $\frac{L_U - \bar{x}}{s}\sqrt{\frac{n}{n-1}}$ for ML
$Q_L^* = \frac{\bar{x} - L_L}{s}$ for MLS and $\frac{\bar{x} - L_L}{s}\sqrt{\frac{n}{n-1}}$ for ML

Note that the MVU estimator is sample size-dependent (beta distribution depends on *n*) while the ML and MLS estimators are independent of the sample size. All three estimators converge to the same actual value as the sample size increases ($n \to \infty$).

Multivariate Case

Baillie (1987) extended the work of Lieberman and Resnikoff and determined the MVU estimator of the PC (or the PWL) for multivariate acceptance sampling. Hamilton and Lesperance (1995) presented the ML and MLS estimators of the PC and compared it with the MVU estimator. For the case of uncorrelated variables and equally important quality measures, the% conforming considering all variables is the product of the% conforming of each individual variable calculated using any of Equation 9 or 10 (Baillie, 1987). This is expressed in Equation 11.

$$p = \prod_j p_j \qquad \text{(Eq. 11)}$$

where

p = total process conforming (PWL)
p_j = process conforming (PWL) for variable j calculated using either the MVU, ML, or MLS method

For the case of correlated variables, Baillie (1987) determined the MVU estimator of the PC for the case of multivariate acceptance sampling as:

$$PWL = \hat{p}_{MVU} = \frac{\Gamma\left(\frac{n-1}{2}\right)|R|^{-1/2}}{\Gamma\left(\frac{n-1-m}{2}\right)\pi^{1/2}} \int_{Z_m} \cdots \int (1 - z^T R^{-1} z)^{(n-m-3)/2} \prod_j dz_j \qquad \text{(Eq. 12)}$$

where

$\hat{p}_{MVU}$ = MVU estimator of the PC (or the PWL)
$\Gamma(x)$ = gamma function
$\boldsymbol{R}$ = $m \times m$ sample correlation matrix
n = total number of samples
m = total number of variables
Z_m = region of intersection of m-dimensional ellipsoid $z^T R^{-1} z \leq 1$ and m-dimensional rectangle $l \leq z \leq u$

$$u = (u_1, \ldots, u_m)^T$$
$$l = (l_1, \ldots, l_m)^T$$
$$u_i = \frac{U_i - \bar{x}_i}{s_i} \frac{\sqrt{n}}{n-1}$$
$$l_i = \frac{\bar{x}_i - L_i}{s_i} \frac{\sqrt{n}}{n-1}$$

The procedure requires that $n \geq m + 2$. Hamilton and Lesperance (1995), argued that the evaluation of the integral is quite difficult even for the case of $m = 2$. An alternative to using the MVU estimator is to use the ML estimator. In this case, the PC can be estimated as:

$$\hat{p}_{ML} = \underset{A_m}{\int \dots \int} \phi_m(\mathbf{x}; \hat{\boldsymbol{\mu}}; \hat{\boldsymbol{\Sigma}}) \prod_j dx_j \qquad (13)$$

where

$\phi_m(\mathbf{x}; \hat{\boldsymbol{\mu}}; \hat{\boldsymbol{\Sigma}}) =$ m-dimensional multivariate normal distribution
$\hat{\boldsymbol{\mu}} = \bar{\mathbf{x}}$ is the sample average
$\hat{\boldsymbol{\Sigma}} = \left(\Sigma \mathbf{x}_i \mathbf{x}_i^T - n\bar{\mathbf{x}}\bar{\mathbf{x}}^T\right)/n$ is the sample covariance matrix
A_m = m-dimensional conformance region.

If the characteristics have lower and upper specification limits, denoted L_i and U_i for i = 1,…,m, then A_m is the m-dimensional rectangle. The procedure is valid for $n \geq m + 1$.

Comparison of the MVU and ML Estimators

Hamilton and Lesperance (1995) compared the MVU and ML estimators of the PC. They investigated the operating characteristic (OC) bands, the practical considerations in the application of each method, the acceptance regions, and the properties of the estimators. Their results are summarized as follows:

1. *OC Bands:* Narrow OC bands are desirable as this ensures that producers with equal overall quality are treated the same. It also ensures that, for the most part, lots of higher quality has a higher probability of acceptance than lots of lower quality. For most of the cases investigated, the MVU method yielded slightly narrower OC bands.

2. *Practical Considerations:* In multivariate acceptance sampling, the estimation of the PC (or the PWL) requires the evaluation of a multidimensional integral (Equations 12 and 13). For the ML and MLS methods, this involves integrating the m-dimensional normal distribution over an m-dimensional hypercube. This is easily performed by numerical software such as MATLAB. For the MVU method, the function to be integrated and the region of integration are much more complicated. As a result, Monte Carlo integration seems the only practical method, and a very large time-consuming simulation is needed for acceptable accuracy.

3. *Acceptance Region:* The acceptance region is defined as the combination of the process mean and standard deviation for which the PC is larger than the acceptable quality level (AQL). In general, when lower and upper specification limits are specified, the maximum allowed standard deviation for acceptance is achieved when the process mean is halfway between the upper and lower specification limits. As the process mean shifts toward either end of the specification limits, the maximum allowed standard deviation decreases. This is true for the double specification-limit univariate case except for the MVU method with n=3. In this case, the maximum allowed standard deviation occurs at values for the mean process slightly shifted

away from the middle of the specification limits (which most of the time represents the target value). This can be illustrated for specification limits on a mix VTM. Suppose the target VTM is 4% with upper and lower specification limits of 5 and 3%, respectively. If the sample number n=3, the contractor is then encouraged not to achieve the 4% VTM but a lower or a higher VTM value between 3 and 5%. The exact amount of shift is dependent on the AQL.

4. *Properties of the Estimators:* It was observed that, for most cases, the difference between the ML estimator of the PC and the actual PC is lower than the difference between the MVU estimator of the PC and the PC. The same can be said for the MLS estimator versus the MVU estimator.

Application to the VDOT VTM, AC, and VMA Data

The comparison of the different methods was performed using the SM9.5 data for the years between 2006 and 2008, including all districts and asphalt plants. The mean and covariance of the data set is presented in Table 7. These are assumed to represent the population parameters (since they represent more than 5,000 data points). The upper and lower limits are also presented in Table 7. These were chosen as the 95% confidence interval for each quality measure based on the calculated standard deviations. The actual PWL, assuming uncorrelated data, can therefore be calculated using Equation 11. This will be 0.8574 (0.95^3). The actual PWL, assuming correlated data, can be calculated using Equation 13. This was calculated as 0.8747.

Table 7. Statistical parameters used for the simulation

		VTM	AC	VMA
Mean		3.43	5.30	16.15
Covariance	VTM	0.753	-0.062	0.526
	AC	-0.062	0.096	0.108
	VMA	0.526	0.108	0.843
Upper specification Limits		5.13	5.91	17.94
Lower specification Limits		1.73	4.69	14.35

A numerical simulation of 500 tests each comprising six samples randomly selected from the multivariate normal distribution with parameters presented in Table 7 was performed using the MATLAB. For each test, the PWL was calculated using the MVU estimator and the ML estimator, assuming both correlated and uncorrelated data, and then compared to the actual PWL (0.8747). For correlated data, the MVU estimator is calculated using Equation 12 while the ML estimator is calculated using Equation 13. The distribution of the calculated PWL is presented in Figure 10. Figure 10 shows that the ML estimator of the PWL produced more results between 0.82 and 0.94 than the MVU estimator. The average PWL for the ML and MVU estimators were 0.8797 and 0.8781, respectively, showing that the average of the MVU estimator was slightly closer to the actual value of 0.8747. Of the 500 simulated tests, the ML method gave a PWL that is closer to the actual PWL in 439 of the cases (88%) when compared to the MVU method. For the calculation of the PWL, the ML method requires the evaluation of the cumulative probability distribution of the multivariate normal distribution, which is already implemented in the MATLAB. For the MVU method, calculation of the PWL requires the evaluation of the integral in Equation 12. The integral was evaluated numerically using the Monte-Carlo integration. A considerable number of points are required for accurate results, and the simulation of 500 tests took more than two hours on a typical desktop computer. Taking into account the method's complexity, computational speed, and accuracy in determining the PWL, the ML method seems to be a viable alternative to the MVU method.

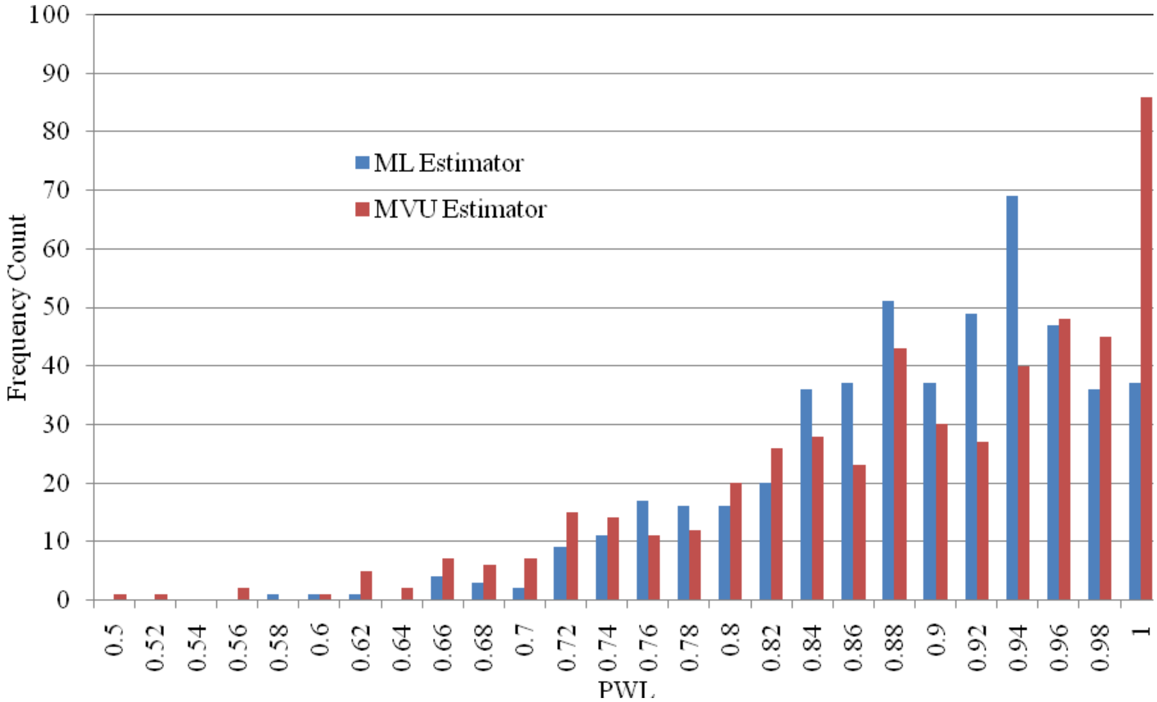

Figure 10. Comparison of multivariate ML and MVU estimators of the PWL

While the ML method for correlated variables is easily implemented in the MATLAB, it is still not convenient for everyday QA applications. When the quality measures are uncorrelated, the PWL is easily calculated using Equation 11 with the individual p_i's calculated as in the case of a single variable. Using Equation 11 to calculate the PWL for correlated data would therefore significantly simplify the analysis, although the method is not 100% correct. This was performed using the MVU and ML methods. The results using the uncorrelated ML method are compared to the results using the correlated ML method in Figure 11. Figure 11 shows that assuming uncorrelated data provides reasonable results compared to when correlation is taken into account. The average results for the ML uncorrelated estimator over the 500 simulated tests is 0.8567 (which is close to the uncorrelated PWL of the population of 0.8574), while the average results for the ML correlated estimator is 0.8797, which is closer to the actual PWL of 0.8747. Of the 500 simulated tests, the ML uncorrelated method surprisingly resulted in a PWL that is closer to the actual PWL in 260 of the cases (52%) when compared to the ML correlated method; however, it resulted in a greater number of low estimates (<0.7) as can be observed in Figure 11. With the results presented here, it seems assuming the VTM, AC, and VMA are uncorrelated is a viable alternative that is very simple to implement and does not lead to significant errors in estimating the PWL. This should, however, be further investigated for more cases of actual PWL and for different levels of correlations.

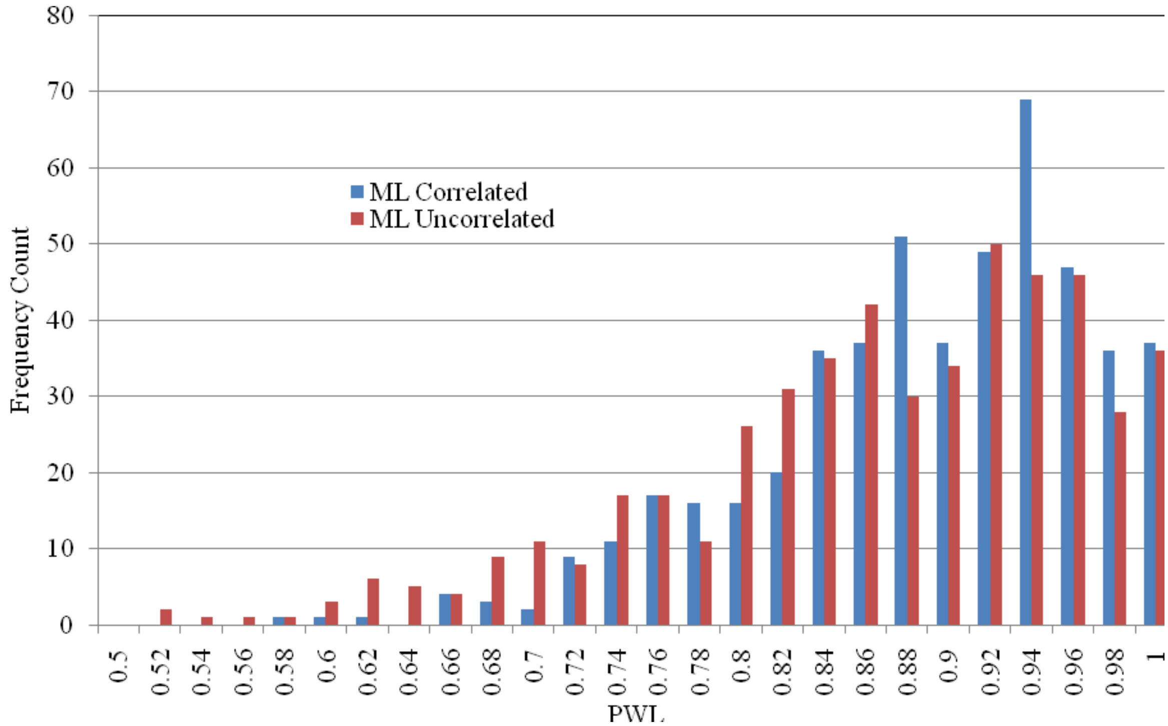

Figure 11. Comparison of a correlated and uncorrelated ML estimator of the PWL

Selecting an Acceptance Plan

Selection of an acceptance plan requires a trade-off between accuracy and complexity. At a minimum, the process mean and variation (standard deviation) should be included such as in the simple plan presented earlier; however, the method does not provide an estimate for the percentage conforming to specifications. For this purpose, the PWL should be used. The PWL allows for univariate or multivariate sampling and estimation methods, including the ML and MVU estimations. Univariate plans can be used along with Equation 11 when variables in a multivariate sampling plan are "uncorrelated" (more practically, have low correlation). The benefits of incorporating correlated measures should be carefully weighed against the complexities introduced in the PWL procedure. From a statistical perspective, correlated variables, depending on the correlation level, do not provide significant new information. For this purpose, the argument to include correlated variables should mainly be based on engineering experience and judgment. In this case, the ML method is a viable alternative to the MVU method as it is simpler to calculate and seems to provide accurate estimations of the PWL. However, the MVU method has the advantage of resulting in slightly narrower OC bands (Hamilton and Lesperance, 1995).

Dynamic Modulus As a Quality Measure

Performance-Related Specifications

In performance-related specifications (PRSs), the acceptance/rejection/pay factor is based on predicted pavement performance in terms of distresses such as rutting or fatigue cracking.

This requires performance prediction models that can relate quality measures (such as the VTM, AC, VMA, and gradation) for the case of the mix or field density, smoothness, and the FWD test results for the case of pavement to predicted pavement performance (such as rutting or fatigue cracking). Variations in the input parameters (the VTM, AC, VMA, smoothness, etc.) will result in variation in the predicted distresses. This can be quantified in terms of reduction or an increase in pavement life and, with an appropriate application of life cycle cost analysis (LCCA) tools, can be translated into monetary values. With the approval of the MEPDG by the AASHTO, the framework for performance prediction models is now available. NCHRP Project 9-22, which is expected to be completed in 2010, takes advantage of these performance prediction models to develop a framework for the PRS. Three advantages of such an approach are as follows:

1. This approach takes material properties as input that results in the prediction of pavement performance. That is, it integrates all the individual quality indicators (the VTM, AC, VMA, smoothness, etc.) into a single value (asphalt concrete rutting, fatigue cracking) that can be used as a basis for pay adjustment.

2. As-designed predicted pavement performance can be compared to as-built predicted pavement performance, which provides actual loss/gain in predicted pavement life. Pay factors can be developed based on the predicted loss/gain of pavement life through the use of life-cycle cost analysis. This will reward contractors that perform better than expected and penalize contractors that perform worse than expected.

3. True PRSs promote innovation and advancement in production and construction methods by rewarding and encouraging contractors that strive to improve the product they deliver.

While the methodology is quite promising, numerous obstacles need to be overcome for successful implementation. Some of these include:

- Calibration of performance prediction models; this requires considerable effort as proper calibration requires high-quality material data and high-quality performance data. These two data sets would need to be linked; i.e., it is essential to be able to identify how certain material parameters affected actual field performance. This can be difficult to obtain as significant performance indicators are usually obtained years after construction.

- Performance prediction models can require more input than what would be practical in a QA program. It is therefore essential to identify which inputs have more variability and are most critical to performance.

- Performance prediction models can take long periods of time to run on a computer. This is the case for the MEPDG, which takes approximately 15 to 25 minutes to run on a typical desktop computer. Considering proper numerical simulations require at least hundreds, if not thousands, of iterations, it is easy to see how this can be a major obstacle.

In NCHRP Project 9-22, a software program to calculate pavement performance was developed based on the MEPDG pre-solved solutions obtained for a number of pavement configurations and material parameters. This allows the simulation to be “instantaneous.” The pre-solved solutions are, however, only valid for conditions similar to the ones investigated in NCHRP Project 9-22, especially for the nationally calibrated performance prediction models. Therefore, NCHRP Project 9-22 is better used as a model framework for VDOT to develop its software based on its calibrated performance prediction models rather than a tool to use for the PRS.

Reduced-Frequency Dynamic Modulus

The dynamic modulus is the principal, asphalt concrete material input property in the MEPDG. It has also been suggested as a simple performance test (SPT) for mix rutting and fatigue cracking. Because of its importance as input to the MEPDG and as a potential SPT, the dynamic modulus would seem to be a natural choice to be part of end-result and performance-related specifications. To this extent, the MEPDG can be used as a QA tool to evaluate the potential variation of asphalt concrete rutting due to variations in the asphalt concrete dynamic modulus. One drawback of using the MEPDG is that it requires the dynamic modulus at a wide range of temperatures and frequencies to determine the asphalt concrete master curve. This is typically achieved with dynamic modulus tests performed during five different temperatures, which would typically require five days of testing. Katicha et al. (2010) have successfully determined an effective reduced frequency for the asphalt concrete dynamic modulus that can be used to estimate the asphalt concrete rutting that would be calculated by the MEPDG. This significantly reduces the amount of testing potentially resulting in significant time and cost savings.

Table 8. Mix design gradation and asphalt content

	Culpeper	**Staunton**	**Salem**
Mix Designation	SM-9.5D	SM-12.5A	SM-9.5D
Binder Content	5.65%	6.00%	5.80%
Sieve	Percent Passing		
¾ in'	-	100	-
½ in'	100	96	100
3/8 in'	90-100	80	90-100
No. 4	80 Max	-	80 Max
No. 8	38-67	36	38-67
No. 200	2-10	5	2-10

Loose asphalt concrete samples were obtained from three different resurfacing projects in the districts of Culpeper, Staunton, and Salem (Virginia). The mix design gradation and asphalt content are presented in Table 8. Samples were collected for every day of mix production to capture production variability and to see how it might affect asphalt concrete rutting performance. From the collected samples, dynamic modulus specimens were produced and tested to determine the master curve. These curves were used to predict the asphalt concrete rutting performance of a typical flexible pavement using the MEPDG and compared to the asphalt concrete rutting performance using the effective reduced frequency.

Specimen Preparation

Once the mixes were collected, representative samples were used to obtain the maximum theoretical specific gravity (G_{mm}) according to AASHTO T-209. The measured G_{mm} were 2.724, 2.399, and 2.480 for mixes obtained from Culpeper, Staunton, and Salem, respectively. The Superpave gyratory compactor was then used to prepare specimens for testing. A target VTM of 7% ± 1% was intended for all the specimens (after coring and/or cutting) since it is the air voids of newly constructed pavements in Virginia. The amount of material in kg needed to achieve this target VTM was determined from the samples obtained during the first day of production.

This amount was used for the preparation of specimens for the remaining production days regardless of the achieved VTM. It should be noted here that the prepared gyratory specimen is six inches in diameter by seven inches in height. The number of gyrations was left variable to achieve the specified height of seven inches. The prepared gyratory specimen is cut to six inches in height and cored to four inches in diameter to procure the specimen for dynamic modulus testing. The averages (standard deviation) of the VTM for the prepared specimens were 6.70% (0.38%), 4.95% (0.77%), and 6.65% (0.40%) for Culpeper, Staunton, and Salem, respectively. The average VTM for Staunton fell outside the target VTM of 7% ± 1% although the VTM of each individual specimen prepared from samples obtained on the first day of production fell within the target limits.

Test Results

Figures 12 through 14 show, on a logarithmic scale, the dynamic modulus master curves for the mixes from Culpeper, Staunton, and Salem, respectively. These plots were obtained from test results presented in Appendix B. Average master curves obtained from each project are presented in Figure 15.

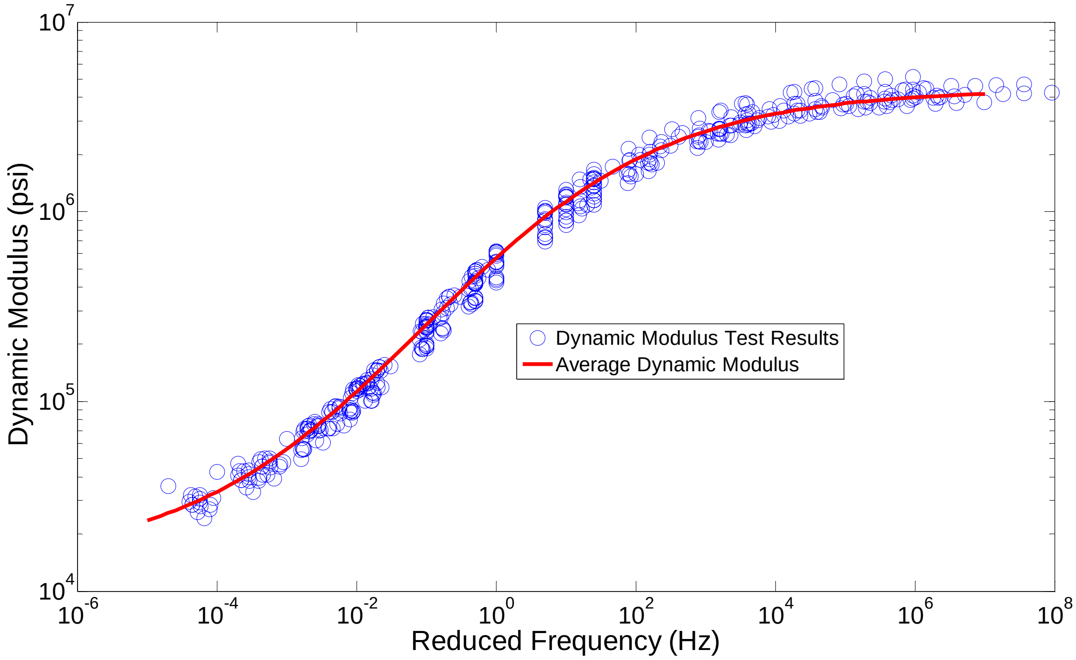

Figure 12. Dynamic modulus master curves for Culpeper mixes

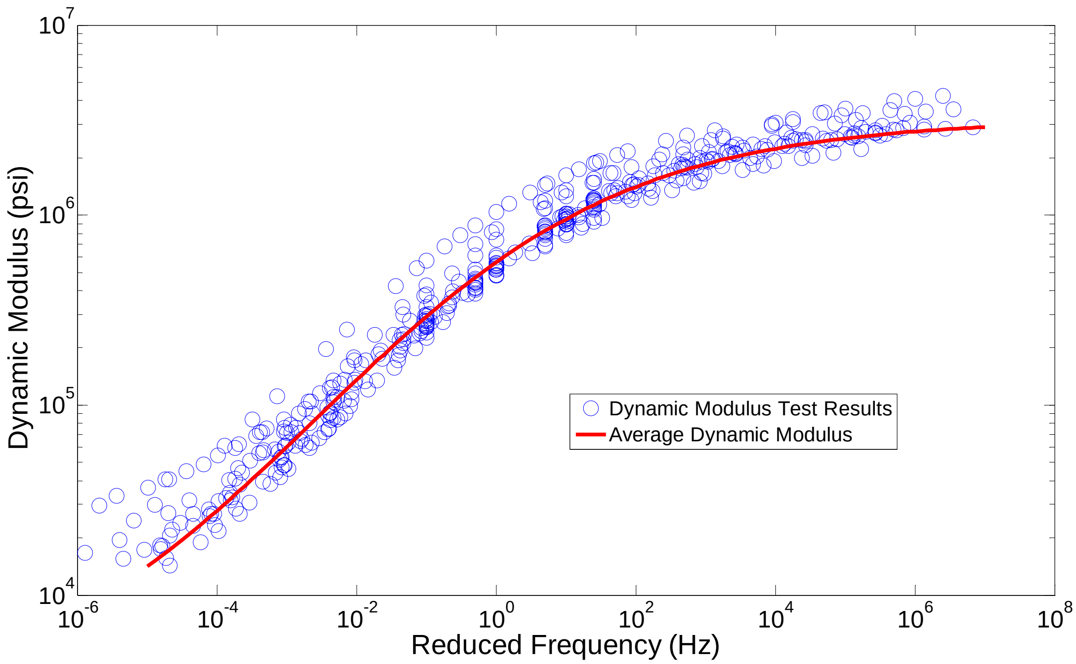

Figure 13. Dynamic modulus master curves for Staunton mixes

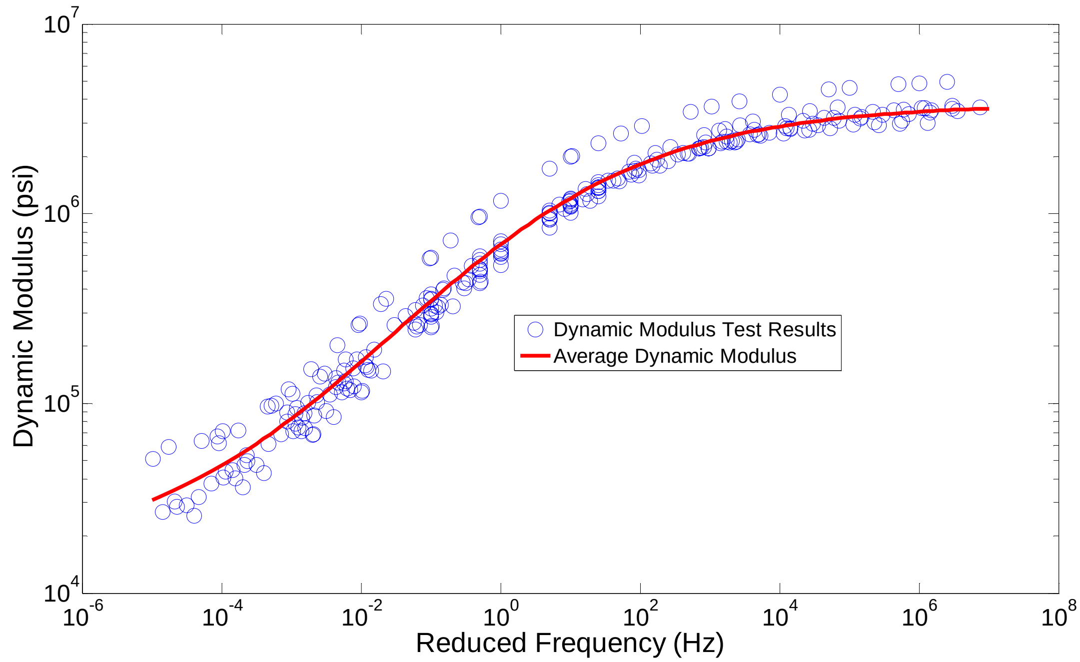

Figure 14. Dynamic modulus master curves for Salem mixes

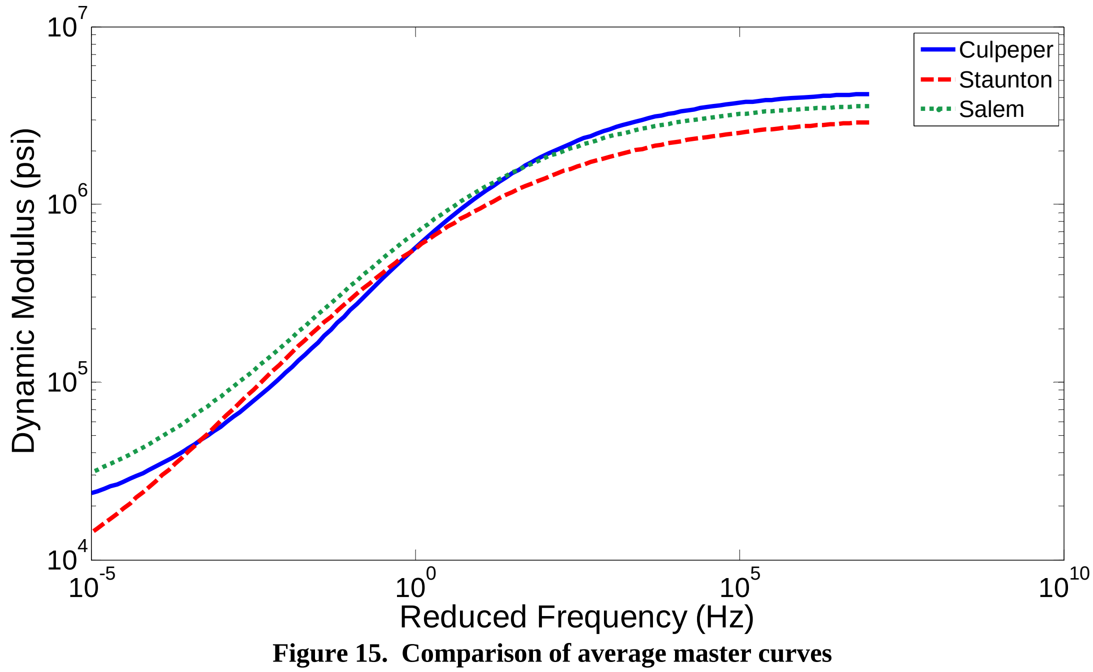

Figure 15. Comparison of average master curves

Determination of Asphalt Concrete Rutting

The procedure by which the effective reduced frequency was determined is presented in Katicha et al. (2010). The suggested reduced frequency was 1 Hz at the reference temperature of 21.1°C (70°F). A power function was found to best relate asphalt concrete rutting to the dynamic modulus as follows:

$$R_{HMA} = aE^b \tag{14}$$

where

R_{HMA}	=	rutting in the asphalt concrete layer (measured in mm)
E	=	dynamic modulus (in GPa) calculated at the effective reduced frequency
a, *b*	=	regression coefficients

The effective reduced frequency and parameters *a* and *b* where determined for a typical flexible pavement presented here:

Traffic

- Two-way average annual daily trick traffic (AADTT): 2000
- Lanes in design direction: two
- Percent of trucks in design direction: 50%
- Percent of trucks in design lane: 95%
- Operational speed: 65 mph
- Traffic growth: 4% compound
- Design years: 20 years
- Other parameters are taken as default values

Structure

- Number of layers: three
- Asphalt concrete layer (Level 1): variable thickness, PG64-22 (binder)
- Granular base A-1-b (input level 3): 152 mm (thickness), 262 MPa (modulus)
- Subbase (input level 3): 52 MPa (modulus)

Asphalt concrete layer thicknesses investigated by Katicha et al. (2010) were 51, 102, 152, and 254 mm. The parameters *a* and *b* are as presented in Figure 16, while the effective reduced frequency was 0.84 Hz for the cases of 102, 152, and 254 mm asphalt concrete layer and 2.1 Hz for the case of 51 mm asphalt concrete layer. These reduced frequencies provide a quality correlation between dynamic modulus and asphalt concrete rutting (Figure 16). Katicha et al. (2010) suggested using an effective reduced frequency of 1 Hz as it is a frequency currently used for dynamic modulus testing, and it does not significantly affect the accuracy. Figure 17 shows that changing the effective reduced frequency from 2.1 Hz to 1 Hz for the case of 51 mm asphalt concrete layer does not significantly affect the accuracy of the model (R^2 = 0.978).

Two asphalt concrete thicknesses were analyzed with a subset of 29 master curves (from all tested master curves) to compare the predicted asphalt concrete rutting using the MEPDG and the predicted asphalt concrete rutting using Equation 14. The two thicknesses were 152 mm and 127 mm. For the case of the 152 mm asphalt concrete layer, parameters *a* and *b* had been obtained and were used to calculate the asphalt concrete rutting obtained from the model using the effective reduced frequency. For the case of the 127 mm asphalt concrete layer, values for *a* and *b* were not obtained, and the asphalt concrete rutting using the effective reduced frequency was obtained by interpolating values obtained for the 152 mm and 102 mm asphalt concrete layers.

The comparison between the predicted asphalt concrete rutting using the effective reduced frequency and the MEPDG calculated rutting is presented in Figure 18. The agreement between the two methods of asphalt concrete rutting calculation is very reasonable. The average deviation between the two methods was 6.8% with a maximum deviation of 23.6%. The deviations in most of the cases (80%) were, however, less than 10%. These numbers are very reasonable considering the typical ability of the MEPDG to predict the actual field rutting even after local calibration. This shows that measuring the asphalt concrete dynamic modulus at the corresponding effective reduced frequency (temperature-frequency combination) would result in time and money savings with minimal loss of accuracy. Moreover, the use of a test temperature (21.1°C) that is in the range of room temperature can decrease temperature conditioning time. Savings in testing can become significant if the test is used on a regular basis for mix QA during production.

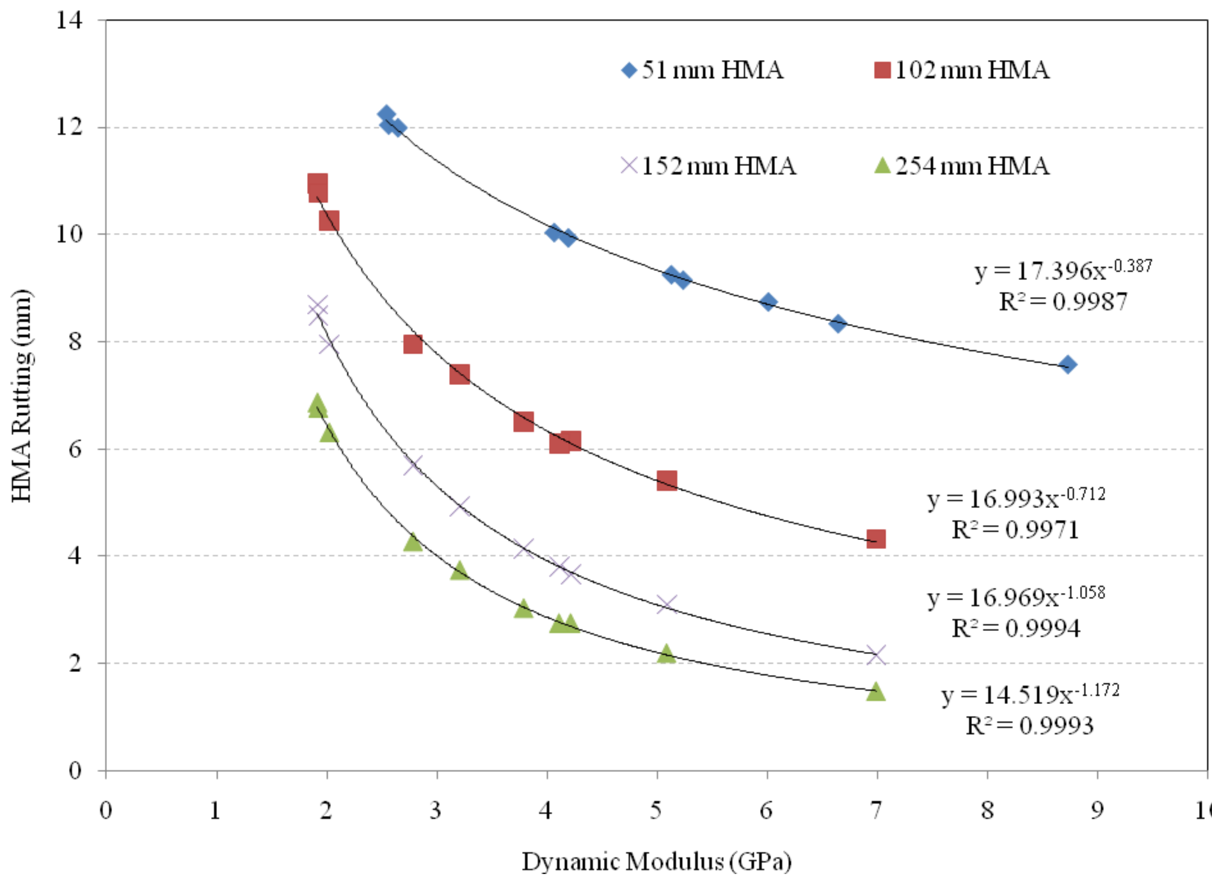

Figure 16. Layer thickness effect on effective reduced frequency

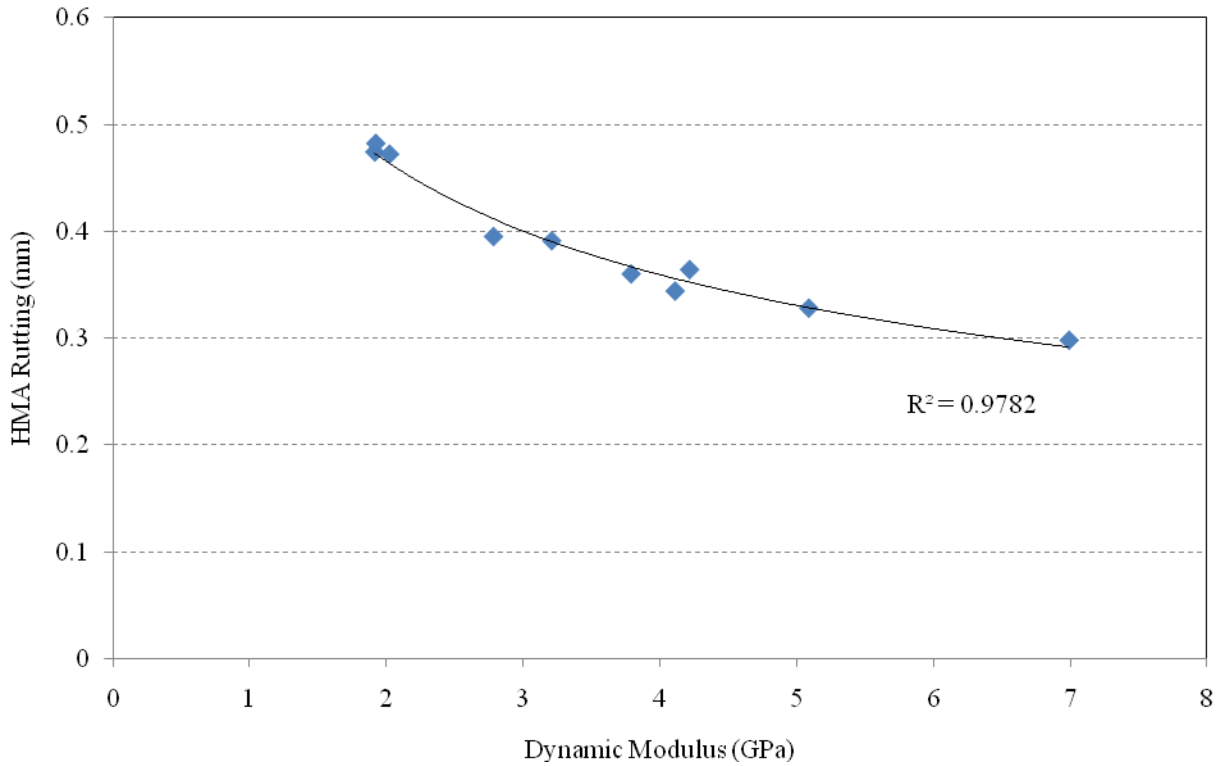

Figure 17. Relationship between dynamic modulus and asphalt concrete rutting for a 51 mm asphalt concrete layer and a 1 Hz effective reduced frequency

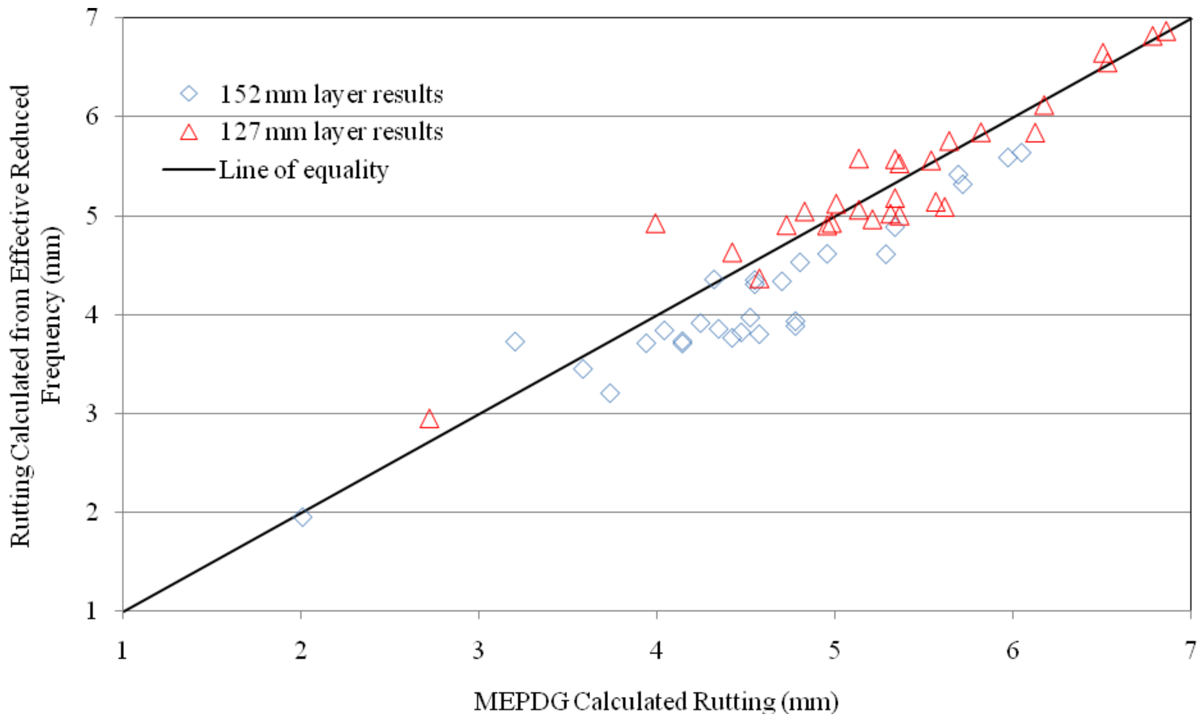

Figure 18. Effective reduced frequency rutting versus MEPDG calculated rutting

CONCLUSIONS

- *For all practical purposes, the VTM, VMA, and AC can be considered normally distributed*. Although only the AC data distribution passed one of the three normality tests, deviations from normality for all three properties seem to be relatively small to considerably affect calculation results. The developed confidence intervals for each property can be used to set specification realizable limits in a quality acceptance plan.

- *The VMA does not add significant new information to that provided by the VTM and AC regarding mix characteristics.* A statistical analysis of the VDOT production data demonstrated the VMA to be highly correlated with the VTM and AC. Including the VMA in an acceptance plan should be based on engineering considerations that clearly show its benefits relative to the introduced complexity in the analysis of the data.

- *Choosing quality characteristics that have low correlation greatly simplifies the calculation of the PWL so that the main procedure is similar to the case of a single variable*. The multivariate ML method can be a much simpler alternative to the MVU method to estimate the PWL when quality measures are highly correlated. Additionally, the ML method seems to be slightly more accurate in estimating the PWL.

- *The MEPDG can be used to develop performance-related ERSs as illustrated with the asphalt concrete dynamic modulus for asphalt concrete rutting performance*. The concept of effective reduced frequency allows characterizing the mix dynamic modulus using a single test at room temperature (21.1°C). Because of the current limited availability and price of the dynamic modulus testing machine, the benefit of using the dynamic modulus as a mix quality measure is probably restricted to large-scale projects.

RECOMMENDATIONS

1. *VDOT's Materials Division should implement a multivariate PWL QA plan that incorporates "uncorrelated" quality measures.*

2. *VDOT's Materials Division should consider incorporating performance-related ERSs using the dynamic modulus for large-scale projects once the MEPDG is calibrated*.

3. *VDOT's Materials Division, along with the Maintenance Division and the Virginia Transportation Research Council, should develop a long term study that would link fundamental material properties to pavement performance based on observed field deterioration*. This study will further improve all aspects of pavement engineering; it will improve the calibration of the MEPDG and, therefore, the accuracy and dependability of pavement design; it will result in accurate performance prediction models that can be used in the QA plan and can better identify the variables that have the most significant effect on pavement performance.

COSTS AND BENEFITS ASSESSMENT

The current state of pavement engineering is at the point where mechanistic-empirical models are no longer limited by computing power but rather the availability of a quality pavement performance database that can be linked to a material properties database to be used for proper calibration of these models. Throughout the years, Virginia has played a leading role in the advancement of pavement engineering practices. This leading role has resulted in improved pavement construction practices resulting in better pavement performance. Maintaining this leadership role will ensure that safer, more reliable and more sustainable pavements are built or maintained. Better understanding of pavement performance will result in considerable cost savings throughout the life cycle of the pavement structure, from the design (better design methods), to the construction (better QA plans), to the maintenance and management (more efficient data collection and storage to support better decision making).

The results presented in this research would provide significant benefits to Virginia. First, the analysis of process variation for the VTM, AC, and VMA allows the development of specification limits that are achievable and economically viable. The PWL procedure extended to the multivariate case can properly handle correlation between the variables and places emphasis on uniformity and adequate average quality. If, as recommended in this report, only variables that have low correlation are used, the PWL procedure is essentially the same as the one for the case of a single variable; therefore, the same cost/benefits suggested by Hughes et al. (2007) are applicable in this case. These benefits include (1) more serviceable, long-lasting, and predictable highway systems; (2) effective use of inspection personnel that would be "*available to monitor key production and placements procedures (e.g., joint tacking and surface preparation) that are every bit as important to good performance but are not easily measured upon delivery*"; and (3) reduction in inspection force that results from the use of effective end-result specifications.

ACKNOWLEDGMENTS

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APPENDIX A

CONFIDENCE INTERVALS FOR PROCESS MEAN AND STANDARD DEVIATION

Table A-1. AC confidence interval of mean response for different sample sizes

Sample Size	Confidence Interval for Different Percentages											
	99	**95**	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**	**5**
3	0.45	0.34	0.29	0.22	0.18	0.15	0.12	0.09	0.07	0.04	0.02	0.01
4	0.39	0.29	0.25	0.19	0.16	0.13	0.10	0.08	0.06	0.04	0.02	0.01
5	0.34	0.26	0.22	0.17	0.14	0.11	0.09	0.07	0.05	0.03	0.02	0.01
6	0.31	0.24	0.20	0.16	0.13	0.10	0.08	0.06	0.05	0.03	0.02	0.01
7	0.30	0.23	0.19	0.15	0.12	0.10	0.08	0.06	0.04	0.03	0.01	0.01
8	0.27	0.21	0.17	0.13	0.11	0.09	0.07	0.05	0.04	0.03	0.01	0.01
9	0.26	0.20	0.17	0.13	0.10	0.09	0.07	0.05	0.04	0.03	0.01	0.01
10	0.24	0.18	0.15	0.12	0.10	0.08	0.06	0.05	0.04	0.02	0.01	0.01
12	0.22	0.17	0.14	0.11	0.09	0.07	0.06	0.05	0.03	0.02	0.01	0.01
15	0.20	0.15	0.13	0.10	0.08	0.06	0.05	0.04	0.03	0.02	0.01	0.00
20	0.17	0.13	0.11	0.08	0.07	0.06	0.04	0.03	0.03	0.02	0.01	0.00
30	0.14	0.11	0.09	0.07	0.06	0.05	0.04	0.03	0.02	0.01	0.01	0.00
40	0.13	0.10	0.08	0.06	0.05	0.04	0.03	0.03	0.02	0.01	0.01	0.00
50	0.11	0.08	0.07	0.05	0.04	0.04	0.03	0.02	0.02	0.01	0.01	0.00
100	0.08	0.06	0.05	0.04	0.03	0.03	0.02	0.02	0.01	0.01	0.00	0.00

Table A-2. AC confidence interval for the standard deviation for different sample sizes

Sample Size	Confidence Interval for Different Percentages											
	99	**95**	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**	**5**
3	0.64	0.52	0.46	0.38	0.33	0.29	0.25	0.21	0.18	0.14	0.10	0.07
4	0.58	0.48	0.43	0.37	0.33	0.30	0.27	0.24	0.21	0.17	0.13	0.10
5	0.55	0.46	0.42	0.37	0.33	0.30	0.27	0.25	0.22	0.19	0.15	0.13
6	0.52	0.45	0.41	0.36	0.33	0.30	0.28	0.26	0.23	0.21	0.17	0.14
7	0.50	0.43	0.40	0.36	0.33	0.31	0.28	0.26	0.24	0.21	0.18	0.16
8	0.49	0.43	0.39	0.36	0.33	0.31	0.29	0.27	0.25	0.22	0.19	0.17
9	0.48	0.42	0.39	0.35	0.33	0.31	0.29	0.27	0.25	0.23	0.20	0.18
10	0.47	0.41	0.38	0.35	0.33	0.31	0.29	0.27	0.25	0.23	0.20	0.18
12	0.45	0.40	0.38	0.35	0.32	0.31	0.29	0.27	0.26	0.24	0.21	0.19
15	0.43	0.39	0.37	0.34	0.32	0.31	0.29	0.28	0.26	0.25	0.22	0.21
20	0.41	0.38	0.36	0.34	0.32	0.31	0.29	0.28	0.27	0.25	0.23	0.22
30	0.39	0.36	0.35	0.33	0.32	0.31	0.30	0.29	0.28	0.26	0.25	0.23
40	0.38	0.35	0.34	0.33	0.32	0.31	0.30	0.29	0.28	0.27	0.26	0.24
50	0.37	0.35	0.34	0.32	0.31	0.31	0.30	0.29	0.28	0.27	0.26	0.25
100	0.35	0.33	0.33	0.32	0.31	0.30	0.30	0.29	0.29	0.28	0.27	0.26

Table A-3. VMA confidence interval for the mean response for different sample sizes

Sample Size	Confidence Interval for Different Percentages											
	99	**95**	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**	**5**
3	1.50	1.14	0.96	0.75	0.60	0.49	0.39	0.30	0.22	0.15	0.07	0.04
4	1.29	0.98	0.82	0.64	0.52	0.42	0.34	0.26	0.19	0.13	0.06	0.03
5	1.14	0.87	0.73	0.57	0.46	0.37	0.30	0.23	0.17	0.11	0.06	0.03
6	1.05	0.80	0.67	0.52	0.42	0.34	0.27	0.21	0.16	0.10	0.05	0.03
7	0.99	0.75	0.63	0.49	0.40	0.32	0.26	0.20	0.15	0.10	0.05	0.02
8	0.90	0.68	0.57	0.45	0.36	0.29	0.24	0.18	0.13	0.09	0.04	0.02
9	0.87	0.66	0.55	0.43	0.35	0.28	0.23	0.18	0.13	0.09	0.04	0.02
10	0.81	0.62	0.52	0.40	0.33	0.26	0.21	0.16	0.12	0.08	0.04	0.02
12	0.75	0.57	0.48	0.37	0.30	0.24	0.20	0.15	0.11	0.07	0.04	0.02
15	0.66	0.50	0.42	0.33	0.27	0.22	0.17	0.13	0.10	0.06	0.03	0.02
20	0.57	0.43	0.36	0.28	0.23	0.19	0.15	0.12	0.09	0.06	0.03	0.01
30	0.48	0.36	0.31	0.24	0.19	0.16	0.13	0.10	0.07	0.05	0.02	0.01
40	0.42	0.32	0.27	0.21	0.17	0.14	0.11	0.09	0.06	0.04	0.02	0.01
50	0.36	0.27	0.23	0.18	0.14	0.12	0.09	0.07	0.05	0.04	0.02	0.01
100	0.27	0.21	0.17	0.13	0.11	0.09	0.07	0.05	0.04	0.03	0.01	0.01

Table A-4. VMA confidence interval for the standard deviation for different sample sizes

Sample Size	Confidence Interval for Different Percentages											
	99	**95**	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**	**5**
3	2.15	1.73	1.52	1.27	1.10	0.96	0.83	0.71	0.60	0.47	0.32	0.23
4	1.94	1.61	1.44	1.24	1.11	0.99	0.89	0.79	0.69	0.58	0.44	0.34
5	1.82	1.54	1.39	1.22	1.10	1.01	0.92	0.83	0.74	0.64	0.52	0.42
6	1.74	1.49	1.36	1.21	1.10	1.01	0.93	0.86	0.77	0.68	0.57	0.48
7	1.67	1.45	1.33	1.19	1.10	1.02	0.94	0.87	0.80	0.72	0.61	0.52
8	1.62	1.42	1.31	1.18	1.09	1.02	0.95	0.89	0.82	0.74	0.64	0.56
9	1.58	1.39	1.29	1.17	1.09	1.02	0.96	0.90	0.83	0.76	0.66	0.58
10	1.55	1.37	1.28	1.17	1.09	1.02	0.96	0.90	0.84	0.77	0.68	0.61
12	1.50	1.34	1.25	1.15	1.08	1.02	0.97	0.92	0.86	0.80	0.71	0.64
15	1.44	1.30	1.23	1.14	1.08	1.02	0.98	0.93	0.88	0.82	0.75	0.69
20	1.38	1.26	1.20	1.12	1.07	1.02	0.98	0.94	0.90	0.85	0.78	0.73
30	1.31	1.21	1.16	1.10	1.06	1.02	0.99	0.96	0.92	0.88	0.83	0.78
40	1.27	1.18	1.14	1.09	1.05	1.02	0.99	0.96	0.93	0.90	0.85	0.81
50	1.24	1.16	1.13	1.08	1.05	1.02	0.99	0.97	0.94	0.91	0.87	0.83
100	1.17	1.12	1.09	1.06	1.03	1.01	1.00	0.98	0.96	0.94	0.91	0.88

APPENDIX B

DYNAMIC MODULUS TEST RESULTS

Table B-1. Day 1 dynamic modulus results (psi)

Temperature (°F)	Frequency (Hz)	Culpeper			Staunton			Salem		
		Sample 1	Sample 2	Sample 3	Sample 1	Sample 2	Sample 3	Sample 1	Sample 2	Sample 3
10	25	4,616,577	4,061,090	3,942,166	2,171,397	2,747,664	2,946,375	3,646,607	3,839,400	5,273,653
	10	4,009,793	3,851,424	3,995,718	2,099,213	2,554,939	2,740,394	3,505,680	3,696,291	5,101,058
	5	3,898,304	3,723,290	3,845,190	2,014,581	2,498,834	2,664,674	3,423,912	3,567,022	4,894,721
	1	3,531,939	3,362,312	3,500,883	1,830,605	2,285,690	2,435,661	3,146,962	3,326,225	4,703,301
	0.5	2,757,328	2,433,486	3,336,587	1,716,856	2,185,187	2,327,899	3,112,029	2,343,204	4,384,852
	0.1	3,038,597	2,731,005	2,939,927	1,515,171	1,955,647	2,078,549	2,701,828	2,159,507	4,083,011
40	25	2,730,432	2,604,696	2,848,866	1,491,354	1,822,115	1,964,745	2,543,436	2,851,705	3,811,218
	10	2,456,758	2,384,996	2,492,496	1,341,718	1,629,636	1,746,664	2,285,287	2,606,866	3,451,141
	5	2,255,534	2,176,792	2,295,549	1,223,120	1,458,396	1,635,439	2,102,219	2,441,237	3,150,130
	1	1,795,761	1,733,770	1,772,992	970,826	1,205,479	1,332,962	1,758,628	2,054,885	2,734,615
	0.5	1,597,498	1,160,651	1,580,644	858,795	762,956	1,224,083	1,603,234	1,875,634	2,290,502
	0.1	1,178,658	1,088,348	1,113,629	639,420	848,653	913,865	1,238,900	1,475,138	1,953,249
70	25	1,215,203	1,066,405	1,124,437	1,002,560	1,119,066	1,030,763	1,191,487	1,434,579	2,594,715
	10	985,332	855,843	887,297	839,739	943,621	852,335	998,261	1,179,949	2,250,575
	5	821,559	706,468	725,902	724,531	821,377	729,842	841,389	1,000,504	1,983,265
	1	525,674	435,308	438,942	490,782	557,747	485,164	557,365	646,125	1,392,396
	0.5	412,150	329,980	336,063	396,239	455,725	390,753	436,886	513,148	1,132,038
	0.1	247,514	193,699	194,320	240,149	273,214	234,602	249,765	290,515	711,859
100	25	419,254	347,084	325,232	259,989	297,567	283,655	447,481	458,580	1,396,120
	10	303,358	238,248	230,496	198,371	247,182	210,549	335,882	340,490	937,578
	5	235,370	183,620	177,257	158,296	193,517	165,297	259,570	264,863	733,971
	1	133,028	104,772	99,809	123,580	107,222	89,021	143,503	145,901	417,545
	0.5	102,308	84,425	76,945	132,593	80,808	68,360	110,533	112,408	316,918
	0.1	68,644	58,507	49,439	81,194	109,884	58,360	69,226	71,226	197,582
130	25	128,001	103,553	105,610	94,922	96,658	82,905	119,844	127,508	NA
	10	90,389	73,744	71,939	64,282	65,850	57,016	83,572	89,947	NA
	5	74,647	61,629	59,105	50,756	64,213	45,138	66,876	72,654	NA
	1	52,095	44,151	41,600	38,834	45,719	31,533	44,131	49,064	NA
	0.5	39,174	31,253	29,895	22,973	37,358	23,025	32,572	36,239	NA
	0.1	34,489	27,471	25,908	38,880	32,719	18,960	27,767	31,488	NA

Table B-2. Day 2 dynamic modulus results (psi)

Temperature (°F)	Frequency (Hz)	Culpeper		Staunton		Salem	
		Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
10	25	4,634,022	3,598,584	3,164,716	2,765,804	3,449,209	3,882,646
	10	4,011,904	4,722,469	2,946,564	2,719,472	3,116,376	3,603,538
	5	3,879,409	4,613,523	2,882,357	2,644,790	3,030,288	3,534,630
	1	3,478,033	4,148,261	2,624,899	2,432,631	2,793,191	3,279,965
	0.5	3,385,839	4,100,966	2,614,831	1,723,544	2,712,838	3,180,548
	0.1	2,961,389	3,546,186	2,339,368	2,144,792	2,480,453	2,866,187
40	25	2,876,013	2,807,461	1,969,494	1,954,957	2,299,614	2,531,717
	10	2,511,177	2,540,722	1,781,551	1,786,294	2,113,027	2,342,084
	5	2,359,959	2,375,055	1,707,207	1,665,085	1,946,581	2,129,674
	1	1,856,657	1,843,354	1,427,048	1,411,599	1,639,679	1,772,190
	0.5	1,243,439	1,339,662	1,342,813	956,106	1,492,635	1,627,711
	0.1	1,201,460	1,214,758	1,022,701	1,024,833	1,161,102	1,256,775
70	25	1,164,955	1,180,615	1,114,823	1,160,071	1,231,574	1,351,966
	10	921,860	929,431	932,805	1,000,690	1,059,663	1,133,038
	5	756,325	764,350	801,484	871,841	919,655	964,134
	1	452,113	459,918	545,090	605,324	618,268	630,889
	0.5	340,569	351,507	440,075	495,863	495,053	500,604
	0.1	192,482	197,235	273,857	305,870	295,325	297,110
100	25	348,588	354,022	359,297	385,396	447,214	451,991
	10	240,311	245,162	264,870	300,763	330,887	329,915
	5	182,525	187,732	205,725	262,290	258,084	254,349
	1	98,726	104,839	109,855	138,646	144,844	141,972
	0.5	76,948	82,760	85,502	100,219	110,729	108,650
	0.1	78,192	56,805	55,185	58,013	84,862	105,393
130	25	129,917	122,063	98,966	120,147	133,560	120,427
	10	90,448	86,725	64,047	77,440	88,761	85,116
	5	70,525	71,588	50,930	60,567	70,151	67,872
	1	46,469	49,322	33,111	38,316	101,097	45,075
	0.5	33,969	37,399	24,101	28,430	70,969	33,006
	0.1	28,683	33,606	19,992	23,064	58,707	27,513

Table B-3. Day 3 dynamic modulus results (psi)

Temperature (°F)	Frequency (Hz)	Culpeper		Staunton		Salem	
		Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
10	25	4,641,804	4,780,431	3,040,234	4,602,999	3,552,448	NA
	10	4,246,305	4,825,892	2,934,005	4,302,999	3,784,860	
	5	4,165,463	4,707,958	2,054,510	4,000,000	3,674,486	
	1	3,788,032	4,385,741	1,917,036	3,500,000	3,445,017	
	0.5	3,630,546	4,422,268	1,783,259	3,100,000	2,548,899	
	0.1	3,271,128	3,863,599	1,624,875	2,950,000	2,867,678	
40	25	3,699,380	4,918,435	2,131,808	3,091,056	2,706,351	
	10	3,363,712	4,598,556	1,990,253	3,107,253	2,495,228	
	5	3,352,995	4,474,686	1,400,632	2,945,482	2,289,935	
	1	2,673,393	3,616,735	1,553,067	2,493,399	1,905,755	
	0.5	2,526,603	3,509,613	1,062,939	2,401,826	1,707,088	
	0.1	1,882,585	2,567,151	822,064	1,906,232	1,342,372	
70	25	1,381,512	1,592,264	2,037,343	1,142,189	1,339,825	
	10	1,092,324	1,232,764	1,698,331	961,529	1,113,888	
	5	907,612	1,019,108	1,470,381	826,582	949,696	
	1	555,823	613,848	1,034,563	539,550	628,074	
	0.5	424,677	451,880	874,544	421,506	497,667	
	0.1	232,238	239,580	537,886	243,249	295,348	
100	25	402,744	435,480	646,892	560,719	428,245	
	10	279,278	299,085	527,260	395,892	320,214	
	5	212,279	224,934	436,508	310,274	252,270	
	1	114,177	118,654	248,648	169,321	188,938	
	0.5	87,205	90,127	187,732	125,151	104,919	
	0.1	56,457	92,174	117,931	72,711	67,739	
130	25	129,377	139,572	90,120	120,704	115,078	
	10	89,571	91,661	61,172	87,641	85,715	
	5	71,260	73,195	47,768	66,331	69,795	
	1	46,653	48,150	29,949	38,687	48,409	
	0.5	34,345	35,662	21,420	27,980	38,646	
	0.1	29,008	30,171	18,428	20,705	32,837	

Table B-4. Day 4 dynamic modulus results (psi)

Temperature (°F)	Frequency (Hz)	Culpeper		Staunton		Salem	
		Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
10	25	3,985,383	5,698,776	2,706,370	3,057,456	3,242,991	5,221,518
	10	3,987,583	4,336,314	2,623,927	2,905,942	3,087,167	5,083,287
	5	3,875,227	4,238,071	2,542,562	2,823,622	2,964,808	5,052,921
	1	3,604,426	3,960,198	2,359,365	2,641,241	2,768,875	4,654,891
	0.5	3,520,284	3,841,302	2,257,162	1,927,351	2,598,952	4,860,812
	0.1	3,242,593	3,493,651	2,035,824	2,281,338	2,350,648	4,370,705
40	25	3,312,499	2,756,465	1,884,299	2,116,145	2,400,384	3,893,074
	10	2,923,886	2,524,475	1,722,009	1,894,554	2,139,770	3,633,737
	5	2,733,084	2,323,762	1,564,353	1,764,448	1,988,365	3,474,281
	1	2,200,183	1,867,339	1,300,582	1,469,153	1,672,306	2,843,507
	0.5	1,990,463	1,710,474	1,140,118	1,342,643	1,533,045	2,603,335
	0.1	1,456,953	1,272,107	885,012	1,039,516	1,220,455	2,071,430
70	25	1,324,149	1,303,061	1,495,216	1,170,058	1,359,589	2,213,239
	10	1,061,650	1,033,936	1,422,593	991,400	1,156,622	1,866,252
	5	889,238	860,918	1,246,074	862,928	1,004,176	1,659,995
	1	555,111	535,058	837,955	566,699	691,357	1,182,962
	0.5	424,121	412,596	688,327	447,353	567,423	973,867
	0.1	240,513	231,592	421,595	261,379	361,445	638,617
100	25	513,517	457,647	325,503	345,129	543,359	1,026,523
	10	360,360	329,795	237,625	244,437	416,544	740,951
	5	275,739	254,958	181,519	184,025	329,490	583,394
	1	149,550	140,907	91,488	92,865	190,173	323,526
	0.5	114,105	109,263	68,950	70,499	145,079	249,565
	0.1	71,614	72,197	44,317	44,530	90,123	152,132
130	25	120,110	121,925	86,305	92,857	182,040	419,241
	10	85,851	87,655	56,097	58,092	127,806	243,486
	5	69,261	72,143	42,026	45,669	100,085	187,363
	1	47,243	50,540	26,428	26,179	61,923	118,485
	0.5	34,489	37,310	19,566	18,744	45,545	85,954
	0.1	29,658	32,446	17,071	16,214	34,140	68,984

Table B-5. Day 5 dynamic modulus results (psi)

Temperature (°F)	Frequency (Hz)	Culpeper		Staunton		Salem	
		Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
10	25	4,414,922	4,505,713	2,930,940	2,559,998	3,106,749	4,251,475
	10	4,210,027	4,941,743	2,799,129	1,860,898	2,946,272	3,554,966
	5	4,072,086	4,864,089	1,895,215	1,773,182	2,857,491	3,468,393
	1	3,789,519	4,378,156	1,775,597	1,662,679	2,657,834	3,149,157
	0.5	3,711,970	4,598,109	1,532,229	1,440,878	1,878,751	3,138,196
	0.1	3,299,963	3,932,944	1,382,709	1,311,033	1,772,791	3,057,823
40	25	3,064,140	3,768,231	1,983,721	1,427,599	2,258,182	2,599,037
	10	2,687,199	3,108,253	1,819,674	1,268,659	2,087,831	2,492,509
	5	2,538,100	3,205,003	1,680,062	1,130,816	1,917,990	2,450,388
	1	2,035,957	2,306,665	1,414,609	959,108	1,657,502	1,987,762
	0.5	1,877,629	2,456,771	1,254,539	834,445	1,518,972	1,912,525
	0.1	1,451,936	1,810,445	987,858	684,979	1,202,603	1,442,608
70	25	1,327,229	1,411,137	1,044,949	1,072,100	1,323,309	1,327,752
	10	1,072,329	1,148,448	876,213	926,260	1,174,082	1,114,523
	5	890,129	969,575	746,970	798,037	1,043,001	942,276
	1	560,986	622,627	491,401	533,163	741,061	611,022
	0.5	428,887	474,403	387,368	416,877	602,793	502,810
	0.1	245,649	273,170	231,114	255,792	379,482	398,525
100	25	464,248	493,241	287,084	346,548	487,330	405,424
	10	333,737	333,804	214,447	256,347	374,128	288,704
	5	256,363	257,936	165,421	197,380	297,174	219,396
	1	141,262	140,624	85,014	102,267	167,707	119,995
	0.5	108,880	108,247	65,379	76,923	130,142	155,005
	0.1	70,973	NA	42,994	49,155	78,580	132,842
130	25	131,015	131,145	53,878	90,620	157,330	157,291
	10	92,101	87,326	53,233	60,636	107,656	118,644
	5	73,747	71,096	42,698	46,908	85,046	94,905
	1	51,121	NA	28,070	29,366	54,486	67,891
	0.5	39,225	NA	21,099	20,988	39,897	55,868
	0.1	35,526	NA	18,371	16,905	30,827	44,281

Table B-6. Day 6 dynamic modulus results (psi)

Temperature (°F)	Frequency (Hz)	Culpeper		Staunton	
		Sample 1	Sample 2	Sample 1	Sample 2
10	25	3,079,223	4,184,464	3,017,731	3,929,687
	10	4,184,666	3,500,170	2,925,759	3,661,689
	5	4,000,569	3,473,876	2,856,812	3,518,515
	1	3,697,154	3,232,358	2,631,521	3,283,989
	0.5	3,480,960	3,102,958	2,554,156	2,877,640
	0.1	3,293,959	2,825,289	2,298,466	2,580,195
40	25	3,139,500	2,785,084	2,070,220	2,165,876
	10	2,817,851	2,541,488	1,877,586	1,982,146
	5	2,706,848	2,376,695	1,186,925	1,818,493
	1	2,167,087	2,008,915	1,026,868	1,553,809
	0.5	1,939,487	1,848,767	860,123	1,411,116
	0.1	1,509,807	1,475,879	711,510	1,133,182
70	25	1,516,477	1,543,358	1,149,658	1,160,715
	10	1,242,607	1,204,332	950,083	984,622
	5	1,037,016	998,126	819,126	851,706
	1	625,049	622,080	547,303	577,343
	0.5	473,343	475,224	439,411	459,397
	0.1	264,205	265,427	262,871	282,371
100	25	477,901	502,783	390,793	383,666
	10	344,329	358,384	299,951	293,934
	5	263,469	275,647	236,576	231,610
	1	144,903	148,340	124,665	125,387
	0.5	111,503	112,853	91,984	94,230
	0.1	73,144	72,573	72,170	61,346
130	25	135,482	127,843	96,883	104,223
	10	93,347	85,009	64,906	70,007
	5	74,297	68,659	49,497	54,804
	1	49,253	47,627	31,049	34,243
	0.5	35,497	34,581	23,024	25,314
	0.1	29,969	30,219	18,745	20,523

Table B-7. Day 7 dynamic modulus results (psi)

Temperature (°F)	Frequency (Hz)	Culpeper		Staunton	
		Sample 1	Sample 2	Sample 1	Sample 2
10	25	NA	NA	3,012,546	3,905,948
	10		NA	2,821,571	3,573,988
	5		4,893,368	2,702,495	3,402,659
	1		4,628,523	2,472,032	3,212,487
	0.5		4,949,102	2,304,207	2,729,474
	0.1		4,335,051	2,112,950	2,513,820
40	25	NA	3,239,133	2,008,942	2,449,970
	10		2,985,610	1,853,935	2,335,245
	5		2,929,006	1,736,015	1,593,756
	1		2,358,757	1,431,784	1,840,779
	0.5		2,254,374	1,325,181	1,243,363
	0.1		1,627,231	1,013,856	1,333,819
70	25	1,245,768	1,488,617	1,179,077	1,535,084
	10	1,025,676	1,231,160	1,033,025	1,266,748
	5	860,613	1,040,360	903,683	1,090,028
	1	544,444	636,735	626,822	751,675
	0.5	422,795	480,725	509,287	604,561
	0.1	240,433	259,541	316,662	373,788
100	25	502,783	520,906	365,433	507,923
	10	358,384	373,372	380,254	382,991
	5	275,647	289,094	301,872	302,638
	1	148,340	155,665	167,083	168,821
	0.5	112,853	118,840	125,935	128,798
	0.1	72,573	74,591	73,847	77,195
130	25	116,423	105,835	256,524	172,171
	10	78,826	73,727	172,664	115,660
	5	62,897	58,639	133,931	87,901
	1	42,009	40,413	74,981	50,624
	0.5	30,650	39,345	52,060	36,133
	0.1	26,696	44,873	34,438	26,422