DETERMINING OPTIMUM SAMPLE SIZES WITH RESPECT TO COST FOR MULTIPLE ACCEPTANCE QUALITY CHARACTERISTICS

By

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I would like to dedicate this dissertation to my supporting parents, Joonhee Cho and SungOck Shin and to my wife, Hyeseung Chung and to my son, Leo Seungjae Cho.

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There has been little and limited research done to determine the optimum sample size n for highway construction acceptance plans containing pay adjustment provisions. To optimize the sample size of Acceptance Quality Characteristics (AQCs) with respect to the cost to the agency, an understanding is required of costs of testing and of the cost consequences associated with making a wrong acceptance decision. This study developed an optimization model to determine the sample size. Actual state agency's data were used not only to check the validity of model's assumptions but also draw the conclusions. Among the key conclusions were: (1) The optimum sample size is generally small (n=3) for Percent Within Limits acceptance plans; (2) The degree of correlation among AQCs has a negligible effect on the optimum sample size; and (3) The highway agency tends to underpay contractors through use of its pay adjustment provisions.

Some cautions are presented for state highway agencies planning to use small sample sizes. Agencies are encouraged to perform their own optimization calculations. By doing so, they will gain a better understanding of their acceptance plan systems and

associated costs, and have greater confidence in applying economic decision analysis principles to minimize expected costs and optimize statistical acceptance risks.

CHAPTER
1 INTRODUCTION

1.1 Background

There has been little research done to establish the optimum sample sizes* for today's highway construction acceptance plans containing pay adjustment provisions. One notable recent research project was conducted for the Federal Highway Administration by the Transtec Group, Inc. The purpose of that research was to determine whether today's commonly used sample sizes (i.e., n = 4-7 for most acceptance quality characteristics [AQCs]**) are too small, too large, or about right. The larger the sample size, the lower the risk of making wrong decisions about rejecting, accepting, or assigning a pay factor to a lot. On the other hand, the more sampling and testing performed, the greater the cost and personnel required. If this sample size is too small, the cost consequences in the long run of making erroneous acceptance or pay adjustment decisions would be too high for state highway agencies.

The approach that was taken in that research was one that involved optimization of sample size with respect to minimizing the cost of acceptance plans to the highway agencies. Numerous assumptions were made, and the research conclusions/findings were general in nature. Also, it was anticipated specific questions will need to be answered through further research before appropriate implementation of findings can be done by highway agencies.

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* Within the highway construction community, the term "sample size" refers to the number of samples obtained from a unit of materials or construction. It should not be confused with the physical size or amount of material or construction that is sampled.

** A quality characteristic is an attribute of a unit or product that is actually measured to determine conformance with a given requirement (e.g., asphalt content, density). When the quality characteristic is measured for unit or product acceptance purposes, it is an acceptance quality characteristic.

To optimize the sample size of AQC(s) with respect to the cost to the agency, an understanding is required of costs of testing and the cost consequences associated with making a wrong acceptance decision. An understanding of specific AQCs is also required, including the correlation among AQCs in an acceptance system composed of several individual AQC acceptance plans, as correlation among AQCs may affect optimum sample sizes in an acceptance system. The research described in this thesis deals with determining the optimum sample sizes for multiple AQCs in a pay adjustment acceptance system* and will result in specific recommendations for implementation.

1.2 Problem Statement

The following are some questions that will be addressed:

- What is the optimum sample size n for a selected two-AQC acceptance system such as to minimize the cost to a state highway agency? Today's commonly used sample sizes range between 4 and 7 for most AQCs. This range of sample size is typically established based on practical considerations such as personnel and time constraints. While a sample size within this range may be practical, it is unclear if it is economically optimal.
- What effect does the degree of correlation among AQCs have on the optimum sample size? If two AQCs are correlated, are their optimum sample sizes greater than, the same as, or less than if they were independent AQCs? Quality assurance experts have encouraged state highway agencies to employ independent AQCs, but many agencies still use some correlated AQCs.
- What effect do pay adjustments have on optimum sample size determination?

* A major difference between quality management systems in highway construction and those in other applications is that units of production submitted for acceptance purposes are either rejected, accepted, or accepted with a pay adjustment (either positive or negative).

Do pay increases and pay decreases necessarily balance out in the long run such that the highway agency neither gains nor loses money through use of its pay adjustment provisions, or is there some gain or loss to the agency? Although most state highway agencies have pay adjustment provisions that include pay increases (incentives) as well as decreases (disincentives), for some AQCs only pay decreases are possible in some states.

- How do the costs of sampling and testing compare against the expected cost of the consequences to the state highway agency as a result of a wrong acceptance decision? State highway agencies need an optimization method they can apply on their own acceptance systems. The use of any optimization method to minimize costs requires an understanding of economic decision theory and of costs and cost models.

1.3 Objectives

The objectives of this study are to:

1. Collect real state highway agency data and use the data to determine the optimum sample sizes for two AQCs commonly employed in current highway construction acceptance plans for hot mix asphalt (HMA).
2. Evaluate the degree of correlation between the two AQCs.
3. Determine the effect of having correlated versus uncorrelated AQCs on the determination of optimum sample size.
4. Evaluate pay adjustment system.
5. Compare findings against current practices and make practical suggestions for implementation.

1.4 Scope

The study consists of developing procedures that can be used to determine optimum sample sizes for AQCs and evaluating correlation between AQCs and its effect on optimum sample size. The results from this study are to be compared with state highway agency practice. The overall goal of this study is to minimize, through the use of optimal sample sizes, the cost of state highway agencies' acceptance plans.

1.5 Research Approach

The research approach that was followed in order to fulfill the research objectives mentioned in Subheading 1.3 is described below:

1.5.1 Task 1

Conduct a literature review to (a) identify how AASHTO and state highway agencies determine sample sizes for their acceptance plans (b) critically evaluate the findings from the Transtec Group research, and (c) establish the AQCs to be analyzed for purposes of this study and the degree to which the AQCs are correlated.

1.5.2 Task 2

(1) Drawing on the Transtec Group research, develop an advanced model that will allow determination of optimum sample sizes for HMA concrete.

(2) Develop a procedure that will be used to determine optimum sample size n for a single AQC and multiple (at least two) AQCs.

1.5.3 Task 3

Obtain the necessary state highway agency data needed to apply the advanced optimization model developed in Task 1 in keeping with the procedure developed in Task 2.

1.5.4 Task 4

Analyze the state highway agency data to determine the degree of correlation that is present between the AQCs selected in Task 1.

1.5.5 Task 5

Determine the optimum sample sizes for the state highway agency's single and multiple AQC acceptance plans.

1.5.6 Task 6

Draw conclusions and develop recommendations for how to minimize the cost to state highway agency through the use of optimum sample sizes.

CHAPTER 2
2 LITERATURE REVIEW

2.1 Sample Size

Sample size refers to the number of samples obtained from a unit of materials or construction. State highway agencies commonly use a sample size between 3 and 7 units per lot (Russell et al. 2001, Mahoney and Backus 2000). This range of sample size is typically established based on practical considerations such as personnel and time constraints. While a sample size within this range may be practical, it is unclear if it is economically optimal. When highway construction QA specifications were first being developed in the 60's and 70's, the issue of acceptance sample size was approached several ways.

2.1.1 Central Limit Theorem

In probability theory, the central limit theorem states conditions under which the mean of a sufficiently large number of independent random variables, each with finite mean and variance, will be approximately normally distributed. The central limit theorem also justifies the approximation of large-sample statistics to the normal distribution in controlled experiments. Equation 1 shown in FHWA report "Cost Effectiveness of Sampling & Testing Programs", FHWA/RD-85/030 explained that if a population has a normal distribution with mean μ and standard deviation σ, then the distribution of the means $\bar{x}$ of samples of size n from that population approaches a normal distribution with mean μ and standard deviation $\sigma/\sqrt{n}$ as the sample size n increases. The term $\sigma/\sqrt{n}$ is also called the standard error of the mean (σ_M).

$$Z = \frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}} \quad \text{......} 1$$

Where,

Z = standardized statistic with a mean of zero and standard deviation of one

$\bar{x}$ = sample mean

μ = population mean

σ = population standard deviation

n = number of samples

Equation 1 can be rewritten as:

$$\sigma_M = \sigma / \sqrt{n} \quad \text{......} 2$$

The assumption of a normal distribution for sample means from a normal parent population does not hold for small n; these obey a distribution called a "Student's t-distribution." Small n here might be considered to be n less than 20 shown in Figure 2-1. The methodology does make this distinction in actual practice, using the t-statistic rather than z-statistic.

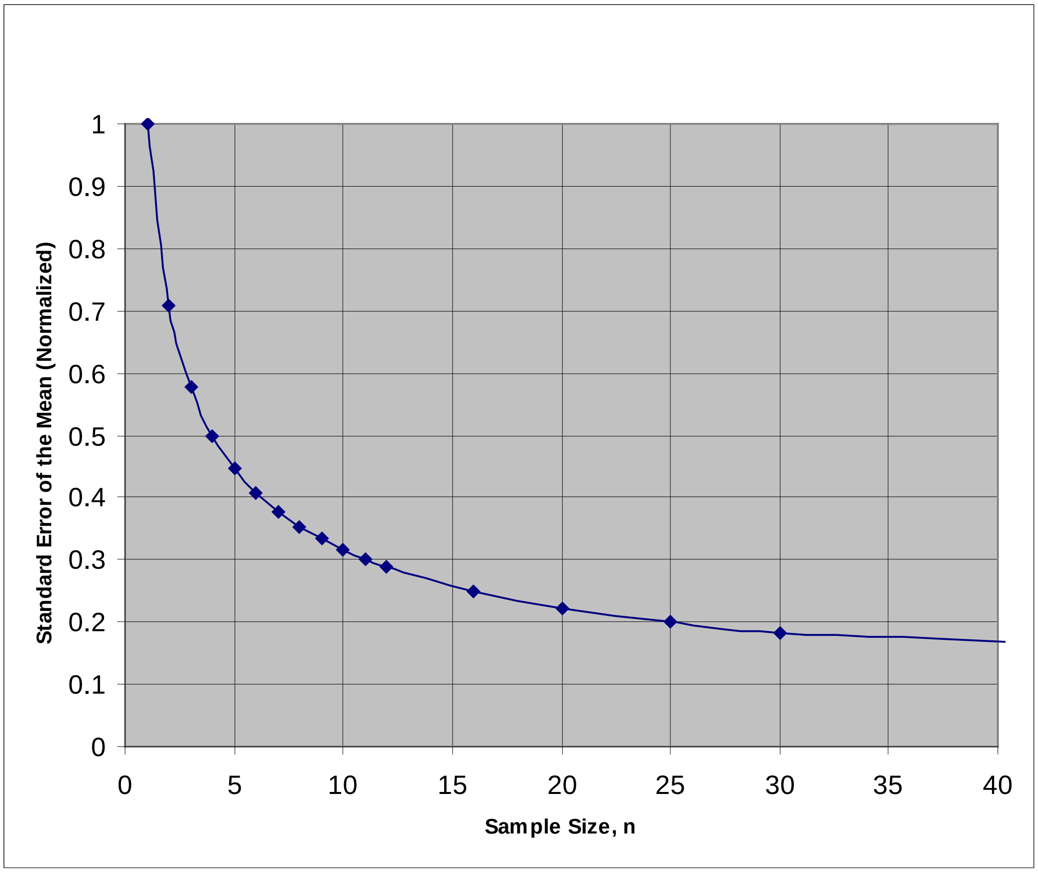


Figure 2-1. Relationship between standard error of the mean and sample size

2.1.2 Statistical Equations

Many statistic text books present Equation 3. The sample size (per lot) required to meet allowable tolerance in the mean (typically stated in the construction specifications), considering both the seller's risk (α) and buyer's risk (β) can be computed as follows:

$$n = \left[\frac{(Z_\alpha + Z_\beta)\sigma}{e} \right]^2 \qquad \text{.........} 3$$

Where

$n =$ sample size

$Z_\alpha =$ standard normal distribution value for the required seller's risk

$Z_\beta =$ standard normal distribution value for the required buyer's risk

$\sigma =$ standard deviation of the population

$e =$ tolerable error allowed by the specifications

ASTM E122-09 "Standard Practice for Calculating Sample Size to Estimate, With Specified Precision, the Average for a Characteristic of a Lot or Process" is intended for use in determining the sample size required to estimate, with specified precision, a measure of quality of a lot or process. The practice applies when quality is expressed as either the lot average for a given property, or as the lot fraction not conforming to prescribed standards. The level of a characteristic may often be taken as an indication of the quality of a material. If so, an estimate of the average value of that characteristic or of the fraction of the observed values that do not conform to a specification for that characteristic becomes a measure of quality with respect to that characteristic. ASTM E122 present equation of the following form for the required sample size, n:

$$n = \left(\frac{3\sigma}{E}\right)^2 \quad \text{.........} 4$$

Where:

$n =$ sample size

σ = the estimate of the lot standard deviation

E = the maximum acceptable difference between the true average and the sample average.

The multiplier 3 is a factor corresponding to a low probability that the difference between the sample estimate and the result of measuring (by the same methods) all the units in the lot or process is greater than E. The value 3 is recommended for general use. With the multiplier 3, and with a lot or process standard deviation equal to the advance estimate, it is practically certain that the sampling error will not exceed E.

These equations have the following limitations to apply to Highway construction Quality Assurance:

1. It does not consider cost.

2. In its current form, it is meant only accept/reject acceptance plan.

3. It applies to estimates of the average, and is not meant for Percent Within Limit (PWL) estimates.

4. It is for a single acceptance plan (one AQC) and not for an acceptance system (more than one AQC). As the number of AQCs increase, the probability of rejecting the lot increases. Thus, as the number of AQCs increases, the probability of rejecting good construction (α risk) increases, and the probability of accepting poor construction (β risk) decreases.

2.1.3 Practical Consideration

Today's' commonly used sample size is typically established based on practical considerations such as personnel and time constraints. From a practical standpoint, a reasonable acceptance sample size is the number of tests the technician(s) can perform in one day (assuming the lot represents one-day's production). This guidance typically results in n = 5 for many AQCs. While a sample size may be practical, it is unclear if it is economically optimal.

2.2 Optimization with respect to Cost

Lapin addressed that whether a sample size is appropriate depends upon (1) the disadvantage of erroneous estimates, and (2) the costs of obtaining the sample. Larger samples are more reliable, but they are also more costly. The costs of obtaining the sample must therefore be balanced against any potential damage from error, as reliability and economy are competing ends.

The risks of error can be considered as having two components: the probability of making them and the consequences they cause. In a sense, implicit costs are incurred when an estimate is erroneous if it leads to consequences that may be damaging. (Lapin, 1975)

In highway construction, it is also very difficult to place cost on the results of an erroneous estimate. Also, the seriousness of an error will vary. A more reliable sample will yield even smaller chances of major error.

Ideally, one should then select a sample size that achieves the most desirable balance between the chances of making errors their costs, and the costs of sampling.

Figure 2-1 illustrates the concepts involved in finding the optimal sample size, which minimizes the total cost of sampling. The costs of collecting the sample data increase with the value of n. But larger samples are more reliable, so that the risks of loss from chance sampling error decline. The total cost of sampling-the sum of collection costs and error costs-will achieve a minimum value for some optimal n. This is the sample size that should be used.

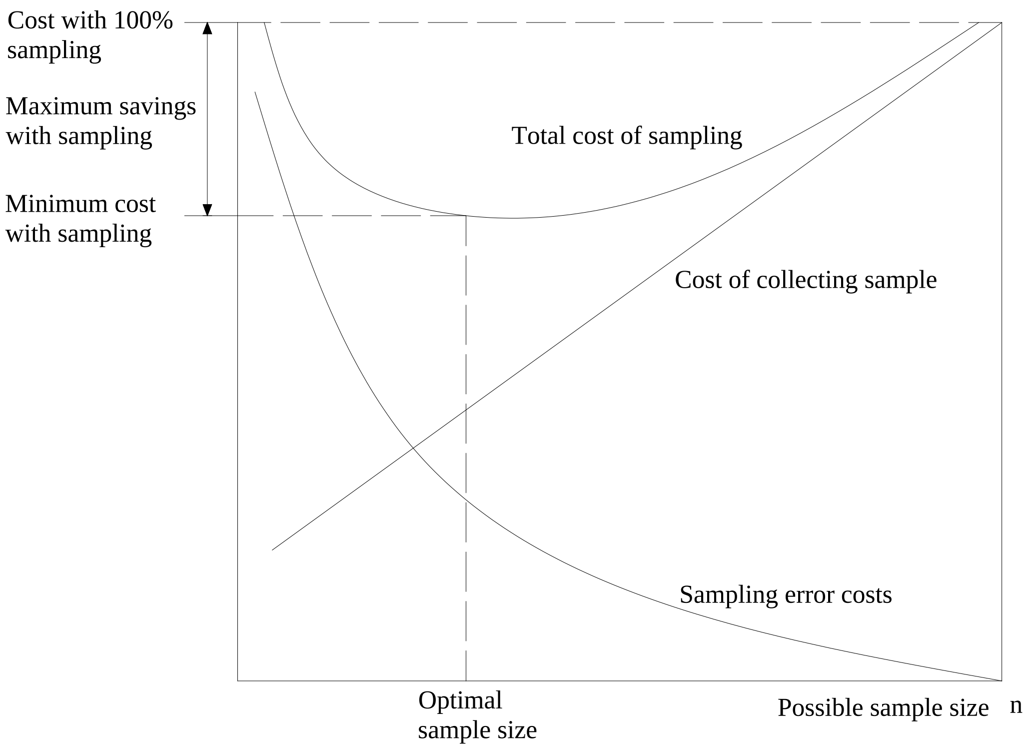


Figure 2-2. Relationship among costs in sampling adapted from Lapin

Because of the difficulties associated with finding the costs of sampling error, the above procedure is not usually used to determine the required sample size in traditional applications. Instead, the focus has been upon a single number that delineates insignificant errors from decidedly undesirable ones, i.e., e in equation 3. This is called the tolerable-error level. In determining this level, one acknowledges that all error is undesirable, but that potential error must be accepted as the price for using a sample *n* instead of the entire population N. There are no guarantees that the tolerable error will not be exceeded. However, large errors may be controlled by keeping the chances of their occurrence small. Furthermore, as indicated earlier, reducing the chance of error increases reliability. Thus, one speaks of reliability in terms of the probability that the estimate will differ from the parameter's true value by no more than the tolerable error.

2.3 Determining Sample Size for PWL Specification

As indicated earlier, previous approaches to determine required sample size are based on average as the measure of quality rather than the PWL measure or any other measure of quality. PWL is considered a preferred measure of quality because it considers both the central tendency and variability in a statistically sound way and Federal Highway Administration (FHWA) also promoted.

2.3.1 Percent Within Limit

The PWL is the percentage of the lot falling above the lower specified limit (LSL), below the upper specified limit (USL), or between the specified limits, as seen in Figure 2-2. PWL may refer to either the population value or the sample estimate of the population value. The PWL quality measure uses the mean and standard deviation in a normally distributed curve to estimate the percentage of population in each lot that is within the specified limit (TRB, 2005).

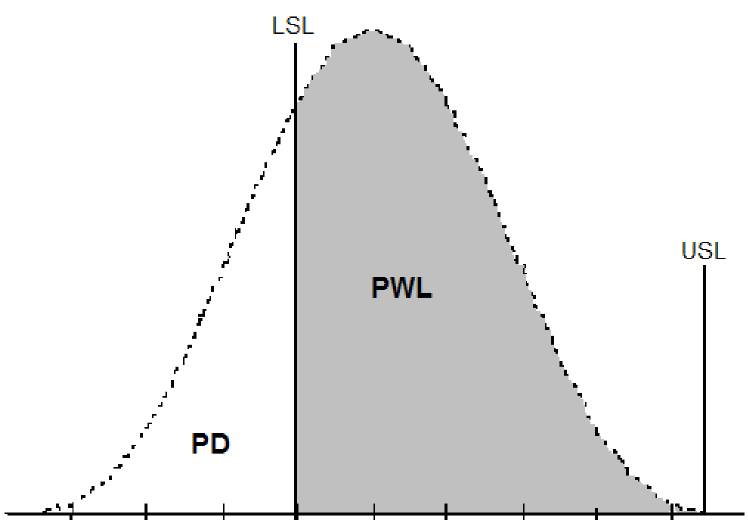


Figure 2-3. Percent Within Limits. LSL = Lower Specified Limit, USL = Upper Specified Limit, PD = Percent Defected, PWL = Percent Within Limits

In practice, it has been found that statistical estimates of quality are reasonably accurate provided the sampled population is at least approximately normal (i.e., bell shaped and not bimodal or highly skewed). The PWL is calculated using the following equation:

$$PWL_i = 100 - PD = \left[1 - B(\alpha, \beta)\left(0.5 - Q_{L_i}\sqrt{\frac{N}{(2(N-1))}}\right)\right] \times 100 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.5$$

Where

PD = percent defective
B(α,β) = beta distribution with parameters α and β
(α,β) = shape parameters of the distribution
Q_{L_i} = lower quality index for an AQC
N = number of samples per lot

Unlike the normal distribution, which is a single distribution that uses the z-statistic parameter to calculate areas below the distribution, the beta distribution is a family of distributions with four parameters alpha (α) and beta (β). The PWL calculation uses the symmetrical beta distribution. For symmetric distributions, the alpha and beta are the same. Figure 2-3 shows three examples of a symmetric beta distribution. As α and β values increase the distributions become more peaked. The uniform distribution has alpha and beta both equal to one. This does not have a well-defined mode because every point has the same probability. Distributions with alpha and beta less than one are bathtub shaped curves and generally not useful for statistical modeling (Ramanathan, 1993)

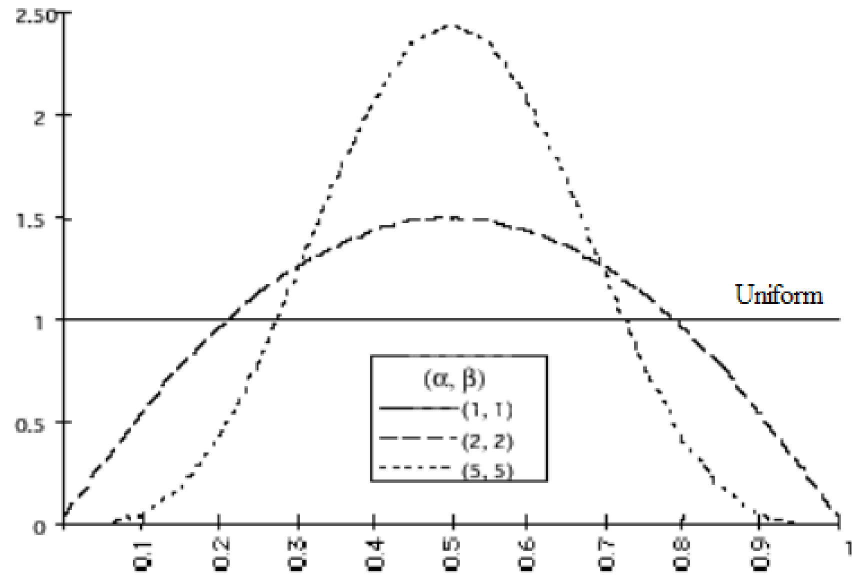


Figure 2-4. Three Examples of Symmetric Beta Distributions

2.3.2 Determining Optimum Sample Size

Recent research (Gharaibeh, 2009) addressed the optimum sample size *n* for pay adjustment acceptance plans and acceptance systems (two or more AQCs) rather than accept/reject acceptance plans and single acceptance plans (one AQC) in previous research. And PWL quality measure was used in this research to determine the optimum sample size for hot-mix asphalt concrete (HMAC) pavement. PWL-based (or PD-based) plans are considered to be advantageous because they take product variability into account and thus promote uniform quality.

CHAPTER 3
3 OPTIMUM SAMPLE SIZE

3.1 Introduction

In this Chapter, recent research by Gharaibeh et al. was used to understand how to determine optimum sample sizes with respect to minimizing the cost of acceptance plans to the highway agencies. At first, his methodology was thoroughly verified. And then, through his optimization model and underlying assumptions, the findings and many questions raised were closely examined. This thesis summarizes that research.

3.2 Optimization Model

Generally a sample size is determined depending upon the disadvantage (cost) of erroneous estimates and the costs of obtaining the sample. The model used by Gharaibeh was come from this concept. To optimize sample size with respect to State Agency's cost, a quantitative relationship must be established between sample size and this cost. Figure 3-1 illustrates the State Agency's total cost of accepting a construction or material lot consisting of two components (Expected cost of erroneous acceptance decision and Cost of sampling & testing).

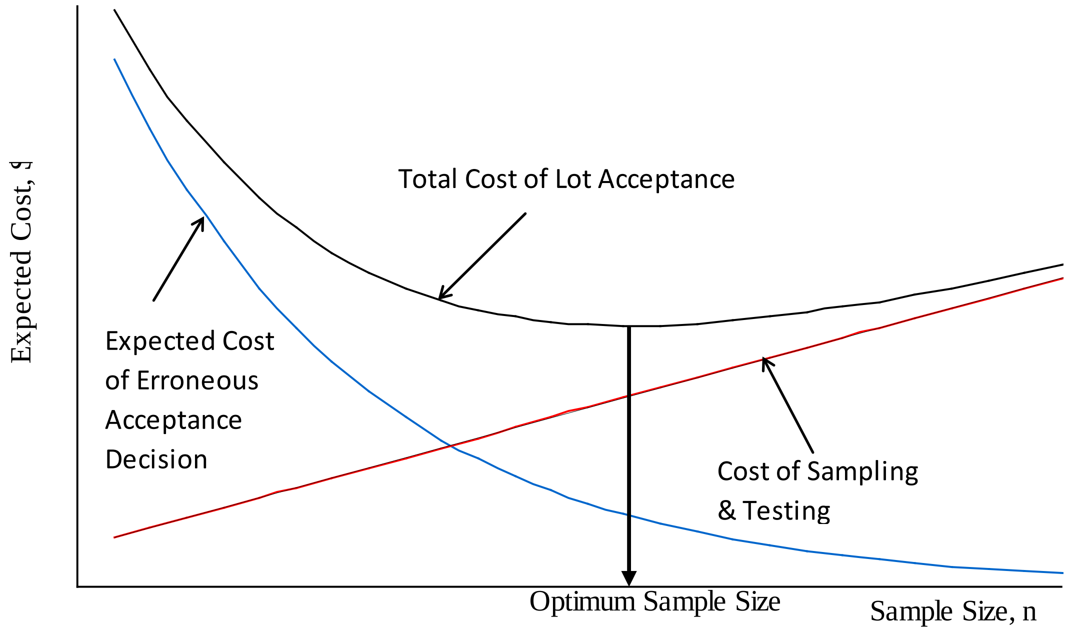


Figure 3-1. Graphical depiction of the sample size optimization concept.

From this model, total cost of lot acceptance can be formulated follows:

Total Cost of Lot Acceptance = $C_T + C_D$ ……………………………………......6

Where, Cost of sampling and testing (C_T)
Expected cost of erroneous acceptance decisions (C_D)

The cost of sampling and testing increases with the value of sample size. But larger samples are more reliable, so that the expected cost of erroneous acceptance decision decline. The total cost of lot acceptance achieves an optimum sample size *n*.

As the cost of sampling and testing increases (i.e. the slope of this cost increases), the curve of total cost of lot acceptance changes and then the optimum sample size would move to the left resulting in a smaller optimum *n*. Similarly, if the expected cost of erroneous acceptance decision were greater, the curve of total cost of lot acceptance would move to the right resulting in a larger optimum *n*.

In his research, the cost of sampling and testing is relatively straightforward and can be computed as follows:

$C_T = n \times m \times c$ 7

Where n is sample size, m is number of replicates, and c is unit cost of testing. The relationship between n and cost of sampling and testing may not be exactly linear in some cases; in those cases where a linearity assumption is not deemed to be appropriate, a discrete function can be applied.

It is also important to understand that while an agency can apply the general model to either a single AQC (a plan) or to multiple AQCs (a system of plans), true optimization can occur only when the agency applies it to the whole system rather than just to a component of the system. Most, if not all, highway agencies have multi-AQC systems. The risks associated with lot acceptance of multi-AQCs are different from those of a single AQC. The more AQCs, the greater the contractor's risk (α) of having good material rejected and the smaller the agency's risk (β) of accepting poor material.

Operating characteristic (OC) curves should be constructed for each quality characteristic to determine if the buyer's and seller's risks associated with the sampling plan are acceptable to the agency and the contractor. The seller's risk (α) is the risk of erroneously rejecting or assigning a payment decrease to a lot that indeed should be accepted or assigned a pay increase. The buyer's risk (β) is the risk of erroneously accepting or not assigning a payment decrease to a lot that indeed should be rejected or assigned a pay decrease. The seller's risk represents the contractor's risk and the buyer's risk represents the highway agency's risk. The graphical representation of an OC curve for accept/reject acceptance plans is shown in Figure 3-2.

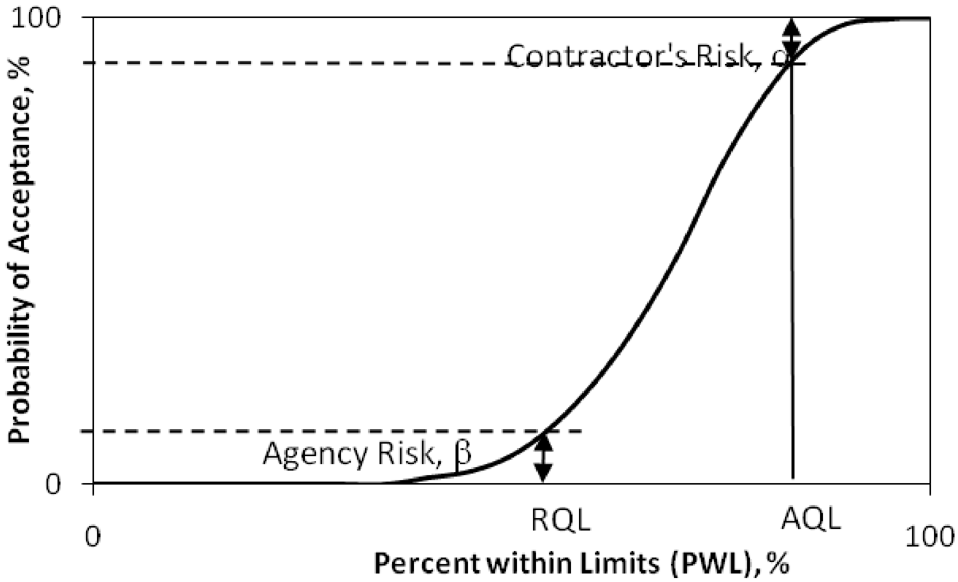


Figure 3-2. Typical OC Curve for Accept/Reject Acceptance Plan

AASHTO R9-05 (AASHTO 2005) suggests that highway agencies should design acceptance plans that control these risks at suitable levels. AASHTO R-9 does not provide specific recommendations for acceptable risk levels, but it states "The more critical the application, the lower should be the buyer's risk. But only under rare circumstances should the buyer's risk be lower than the seller's risk." AASHTO R9-90 (AASHTO 1995), however, indicates that these risks can be set based on the criticality of the measured property as it affects safety, performance, or durability as shown in Table 3-1.

Table 3-1 Acceptable Risk Levels, based on the Criticality of the Inspected Product (AASHTO 1995).

Classification	Buyer's risk at RQL	Probability of acceptance at AQL	Seller's risk at AQL
Critical	0.005	0.950	0.050
Major	0.050	0.990	0.010
Minor	0.100	0.995	0.005
Contractual	0.200	0.999	0.001

A conventional OC curve represents the relationship between PWL (or PD) and probability of acceptance. The statistical procedure for developing OC curves is well-documented in the statistics and probability literature (see for example Duncan 1986). Perhaps one of the most established software tools in the highway construction arena for developing OC curves is the OCPLOT simulation software (Weed 1996).

For acceptance plans with a single AQC, a lot is considered of poor quality if that particular AQC is rejectable [i.e., PWL is at (or below) the rejectable quality level (RQL)]. Thus, the agency's expected cost due to erroneous acceptance decisions is computed as follows:

$$C_D = \beta_{RQL} \times P_{RQL} \times B \times S \quad \text{..........} 8$$

Where

β_{RQL} = buyer's risk (i.e., probability of erroneously accepting a lot that has a true PWL equal to or less than the RQL, computed at midpoint between zero and RQL).
P_{RQL} = proportion of prior lots of rejectable quality throughout the state. This prior distribution of quality can be obtained from the agency's construction quality databases or paper records of past construction projects.
B = unit bid price
S = lot size

For an acceptance plan that considers multiple AQCs, a lot is considered of poor quality if at least one of the AQCs is rejectable (i.e., PWL is at or below RQL). Thus, the agency's expected cost due to erroneous acceptance decisions is computed as follows:

$$C_D = \sum_{j=1}^{l} \left[\beta_i P_i \times \beta_{i+1} P_{i+1} \times .... \times \beta_k P_k\right]_j \times B \times S \quad \text{..........} 9$$

where l is the number of combinations of βP for all AQCs, where e=β_{RQL} and P = P_{RQL} for at least one AQC. Combinations that do not have all AQCs at the RQL are influenced by the acceptable quality level (AQL). Suppose an acceptance plan includes two AQCs, a rejectable-quality lot can occur under any one of the five possible scenarios shown in Table 3-2.

Table 3-2 Probability of Accepting Poor Quality Lot Considering Two AQCs

Scenario	PWL	Probability of Acceptance for any Given Lot	Statewide Historical Occurrence	Statewide Probability of Acceptance
Both AQC1 and AQC2 are rejectable	PWL1≤RQL1 & PWL2≤RQL2	$\beta1_{RQL} \times \beta2_{RQL}$	$P1_{RQL} \times P2_{RQL}$	$\beta1_{RQL} \times \beta2_{RQL} \times P1_{RQL} \times P2_{RQL}$
AQC1 is rejectable and AQC2 is acceptable without pay increase	PWL1≤RQL1 & RQL2< PWL2<AQL2	$\beta1_{RQL} \times \beta2_{RQL\text{-}AQL}$	$P1_{RQL} \times P2_{RQL\text{-}AQL}$	$\beta1_{RQL} \times \beta2_{RQL\text{-}AQL} \times P1_{RQL} \times P2_{RQL\text{-}AQL}$
AQC1 is rejectable and AQC2 is acceptable with pay increase	PWL1≤RQL1 & PWL2≥AQL2	$\beta1_{RQL} \times \beta2_{AQL\text{-}100}$	$P1_{RQL} \times P2_{AQL\text{-}100}$	$\beta1_{RQL} \times \beta2_{AQL\text{-}100} \times P1_{RQL} \times P2_{AQL\text{-}100}$
AQC1 is acceptable without pay increase and AQC2 is rejectable	RQL1< PWL1<AQL1 & PWL2≤RQL2	$\beta1_{RQL\text{-}AQL} \times \beta2_{RQL}$	$P1_{RQL\text{-}AQL} \times P2_{RQL}$	$\beta1_{RQL\text{-}AQL} \times \beta2_{RQL} * P1_{RQL\text{-}AQL} \times P2_{RQL}$
AQC1 is acceptable with pay increase and AQC2 is rejectable	PWL1≥AQL1 & PWL2≤RQL2	$\beta1_{AQL\text{-}100} \times \beta2_{RQL}$	$P1_{AQL\text{-}100} \times P2_{RQL}$	$\beta1_{AQL\text{-}100} \times \beta2_{RQL} \times P1_{AQL\text{-}100} \times P2_{RQL}$

The acceptance plans that have been developed for State Highway Agencies are used to determine accept/reject/pay for all lots that are delivered by the contractor to the state. To optimize n, we need information on how the quality of submitted lots varies within a state. Some states have construction quality databases that can be used to determine the proportions of lots submitted at various estimated quality levels. From these construction quality databases, indications are that few lots are estimated to be RQL, thus few lots are rejected; most lots are estimated to be close to or above the AQL

3.3 Discussion of Assumptions

Gharaibeh assumed some items to balance the complexity of the developed method with the level of accuracy needed to achieve the study's objectives. In this chapter, his assumptions were introduced and further discussion in details will be considered in Chapter 5.

Gharaibeh used three different anticipated lot-quality categories in his calculations shown in Table 3-3. With these lot-quality assumptions, Gharaibeh found optimum n to be very small (3 or less) for all but a few cases under the “regular” and “poor” quality categories for all but a few cases under the “regular” and “poor” quality categories. These categories were based on likely-conservative assumptions because of the absence of specific data (real state agency’s data).

Table 3-3 Inputs for Determining Optimum Sample Sizes for Two AQCs

Input	Historically Poor Quality	Historically Regular Quality	Historically Good Quality
AQL	90%	90%	90%
RQL	50%	50%	50%
M	60 and 70%	60 and 70%	60 and 70%
P_{RQL}	15%	5%	0%
$P_{RQL-AQL}$	85%	90%	85%
$P_{AQL-100}$	0%	5%	15%

He assumed that erroneous acceptance decision is defined as accepting a lot that should have been rejected. It is assumed that erroneous decisions associated with assigning the wrong pay adjustment cancel each other out (i.e., the cost to the state DOT of paying more for a lot than it is worth is offset by the gain to the state DOT of paying less for a lot than it is worth). He essentially treated pay-adjustment acceptance plans as if they were accept/reject acceptance plans. The validity check that the assumption of zero cost of erroneous pay decisions is appropriate will be performed in Chapter 6.

He assumed that AQCs are independent or weakly dependent. This assumption is not unrealistic since contractors tend to pay attention to individual AQCs, rather than combined measures of quality. In other words, if one AQC has poor quality, it does not necessarily indicate that other AQCs also have poor quality. In Chapter 6, the effect of correlated AQCs on optimum n will be investigated.

He assumed a linear relationship between the cost of sampling and testing and sample size n. This cost is hard to model because there are many different possible cost scenarios. The assumption of linearity tends to “average” all the possible cost scenarios that exist within the state and/or within the acceptance plan system.

He also assumed that the agency’s expected cost due to erroneous acceptance decisions is based on bid price, and does not consider other costs such as user costs or future maintenance and rehabilitation costs.

An important third cost element (C_R) was missed from the Gharaibeh model. The C_R can be called as the cost of contractor reaction. This cost can be separate from the two elements: cost of sampling and testing (C_T) and expected cost of erroneous acceptance decisions (C_D). If an agency switches to a smaller n than the one it currently uses, this cost can affect lot cost and quality.

CHAPTER 4

4 PRELIMINARY OPTIMIZATION MODEL AND ANALYSIS

4.1 Introduction

To optimize sample size with respect to the cost to the agency, an understanding is required of costs of testing and the cost consequences associated with making a wrong acceptance decision. An understanding of AQCs is also required, and particularly of the correlation among AQCs in an acceptance system composed of several individual AQC acceptance plans. Correlation among AQCs may affect optimum sample sizes in an acceptance system. Due to absence of state agency's real database preliminarily, fictitious data was created and used as examples of a modified Gharaibeh approach.. These data are presented in Table 4-1.

Table 4-1 Fictitious Data

AQC / Lot Number	AQC1 (PWL)	AQC2 (PWL)
1	70	75
2	100	98
3	90	88
4	100	100
5	95	75
6	80	60
7	100	97
8	91	100
9	100	100
10	80	45
11	48	93
12	99	95

4.2 Preliminary Analysis

4.2.1 Single AQC

The data are categorized to 3 parts of proportion for 2 AQCs respectively since we will use them as input value to compute proportion of prior lots of rejectable quality shown in Table 4-2 and Figure 4-1 and 2 as histograms.

Table 4-2 Category of Fictitious Data

AQC1		AQC2	
Proportion	Class	Proportion	Class
1/6 (17%)	RQL (0~70 PWL)	1/6 (17%)	RQL (0~70 PWL)
1/3 (33%)	AQL (71-91 PWL)	1/4 (25%)	AQL (71-91 PWL)
1/2 (50%)	95 PWL (above 91 PWL)	7/12 (68%)	95 PWL (above 91 PWL)

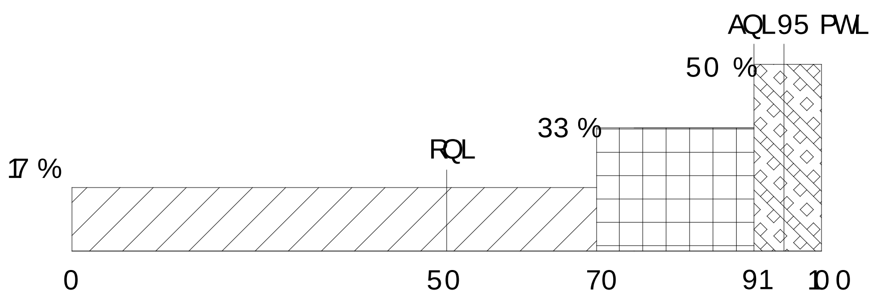


Figure 4-1. AQC1 Histogram

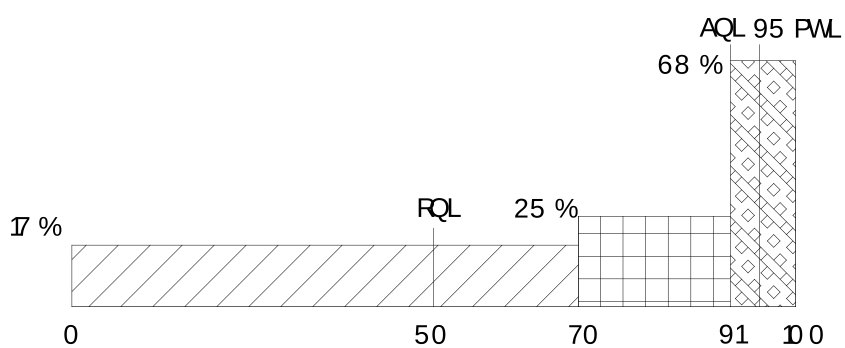


Figure 4-2. AQC2 Histogram

To optimize sample size with respect to State Agency's cost, a quantitative relationship must be established between sample size and these costs. State Agency's total cost of accepting a construction or material lot consists of two components introduced in Equation 6.

For acceptance plans with a single AQC, State Agency's expected cost due to erroneous acceptance decisions is computed as follows:

$C_D = P_r\ (\text{AQC is poor}) \times \beta_{XX} \times \text{Unit Price} \times \text{Lot Size}$ 10

Where,

P_r = proportion of prior lots of rejectable quality
β_{XX} = probability of accepting a lot having xx PWL

Proportion of prior lots of rejectable quality can be found in Figure 4-3.

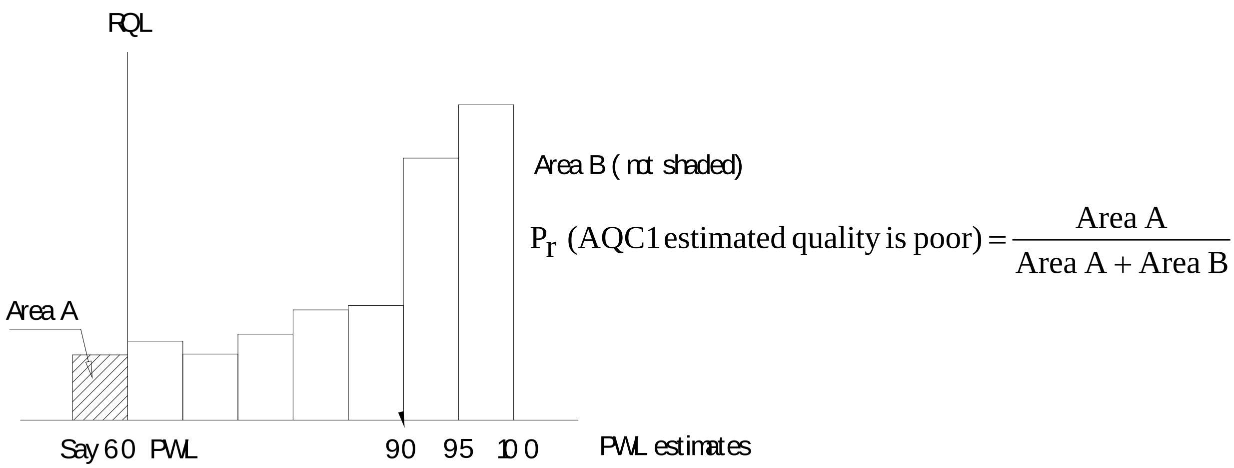


Figure 4-3. Proportion of prior lots of rejectable quality

State Agency has an acceptance plan (AQC1, asphalt binder content) in use, and the database shows that 17 percent of the submitted asphalt content lots are in RQL class, 33 percent are in AQL class, and 50 percent are 95 PWL class. The assumption is made here that there is only one event that can lead to State making an acceptance decision error that has significant negative consequences. That event occurs when the state accepts an RQL lot. FIGURE 5 represents the proportion of lots (0.17) that are RQL.

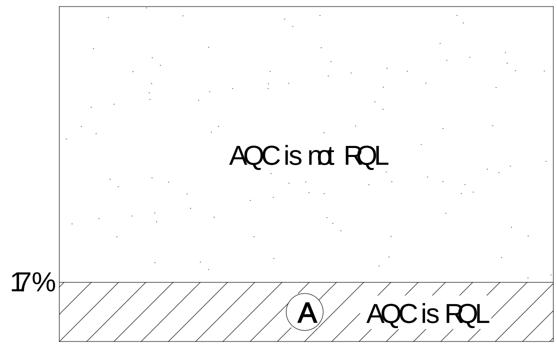


Figure 4-4. Venn Diagram for single AQC

Equation 10 can be computed for cost of making erroneous decisions as follow:

$C_D = 0.17 \times \beta_{50} \times \text{Unit price} \times \text{Lot size}$ …….. 11

In order to obtain probability of making erroneous decision β, OC PLOT (AASHTO R-9, 1990) is used with input values (AASHTO Quality Assurance Guide Specifications, 1996) as follows:

Acceptable Quality Level (AQL) = 90%

Rejectable Quality Level (RQL) = 60%

Acceptance Limit (M) = 70%

Sampling and testing costs (C_T) for asphalt binder content was approximately estimated from an anonymous contractor. Total cost of lot accepting was computed by Equation 6. These procedures have been programmed in an Excel spreadsheet for rapid computation.

As can be seen from Figure 4-5, optimum sample size n for AQC1 is 19.

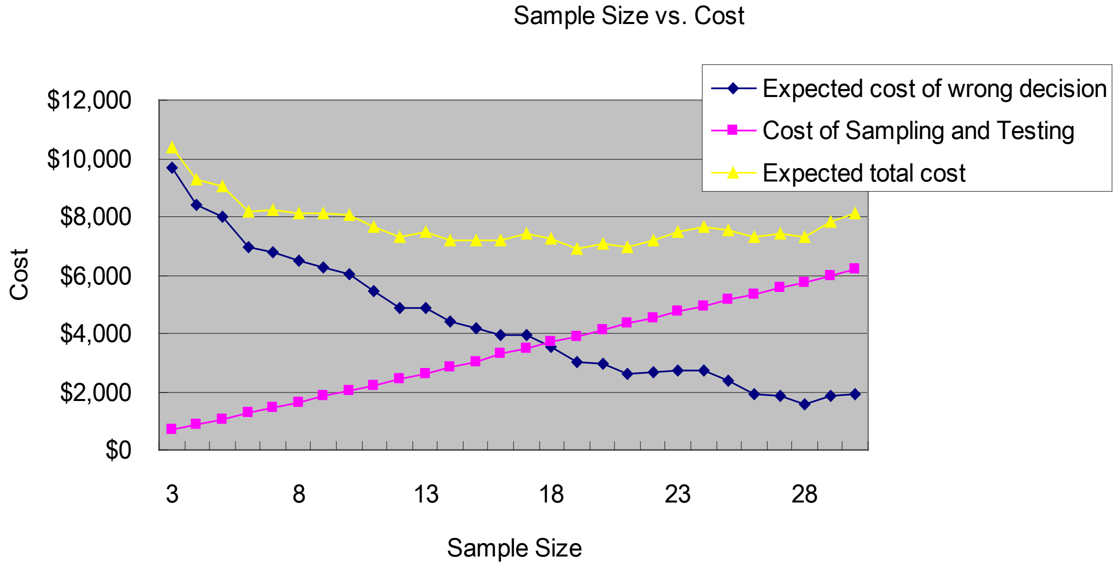


Figure 4-5. Single AQC model for Optimum Sample Size

4.2.2 Independent Double AQCs

State Agency's expected cost due to erroneous acceptance decisions for multiple AQCs consist of two parts. If multiple AQCs are not correlated (i.e., independent), cost equation is computed as follows:

$$C_D = \Sigma(P_{r\ \text{each AQC}} \times \beta_{xx\ \text{each AQC}}) \times \text{Unit Price} \times \text{Lot Size} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots.12$$

Where,

$P_{r\ \text{each AQC}}$ = proportion of prior lots of rejectable quality for each AQC

$\beta_{xx\ \text{each AQC}}$ = probability of accepting a lot having xx PWL for each AQC

State Agency has an acceptance plan system (asphalt binder content and air void, AQC1 and AQC2 respectively) in use, and the database shows that 17 percent of the submitted asphalt binder content lots are in RQL class, 33 percent are in AQL class, and 50 percent are 95 PWL class for AQC1 and 17 percent of the submitted air void lots are in RQL class, 25 percent are in AQL class, and 68 percent are 95 PWL class. All events that can occur are shown in Figure 4-6 as Venn Diagram.

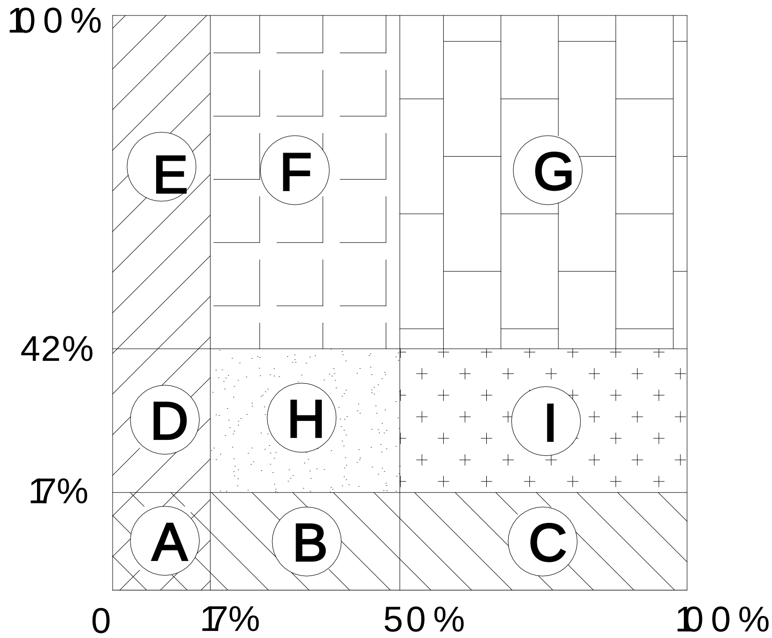


Figure 4-6. Venn Diagram for Independent Double AQCs

All events that can lead to any consequential acceptance decision error by the state (i.e., acceptance of a lot that should be rejected) are as follows:

Event A: Both AQCs come from RQL class

Event B: AQC1 is from AQL class, AQC2 is from RQL class

Event C: AQC1 is from 95 PWL class, AQC2 is from RQL class

Event D: AQC1 is from RQL class, AQC2 is from AQL class

Event E: AQC1 is from RQL class, AQC2 is from 95 PWL class

Note that events F, G, H, and I are inconsequential to us.

We have assumed that the only way the State agency can make an acceptance decision error is by accepting RQL class material. The State cannot make an acceptance decision error when event F, G, H, or I occur. The State can, however, make an acceptance decision error when both AQCs are RQL (event A), when only AQC1 is RQL (events D and E) or when only AQC2 is RQL (events B and C)

For this double AQC case, cost of making erroneous decisions is computed as follows:

C_D = [(1/6)(1/6)$\beta_{50}\beta_{50}$ + (1/6)(1/4)$\beta_{50}\beta_{90}$ + (1/6)(7/12)$\beta_{50}\beta_{95}$ + (1/3)(1/6)$\beta_{90}\beta_{50}$ + (1/2)(1/6)$\beta_{95}\beta_{50}$] $\times$ Unit price $\times$ Lot size ……………………………………………13

As can be seen from Figure 8, optimum sample size n for independent double AQCs is 15. This is the total n for both AQC1 and AQC2 and is considerably smaller than the optimum n of about 19 determined in the single AQC1 example.

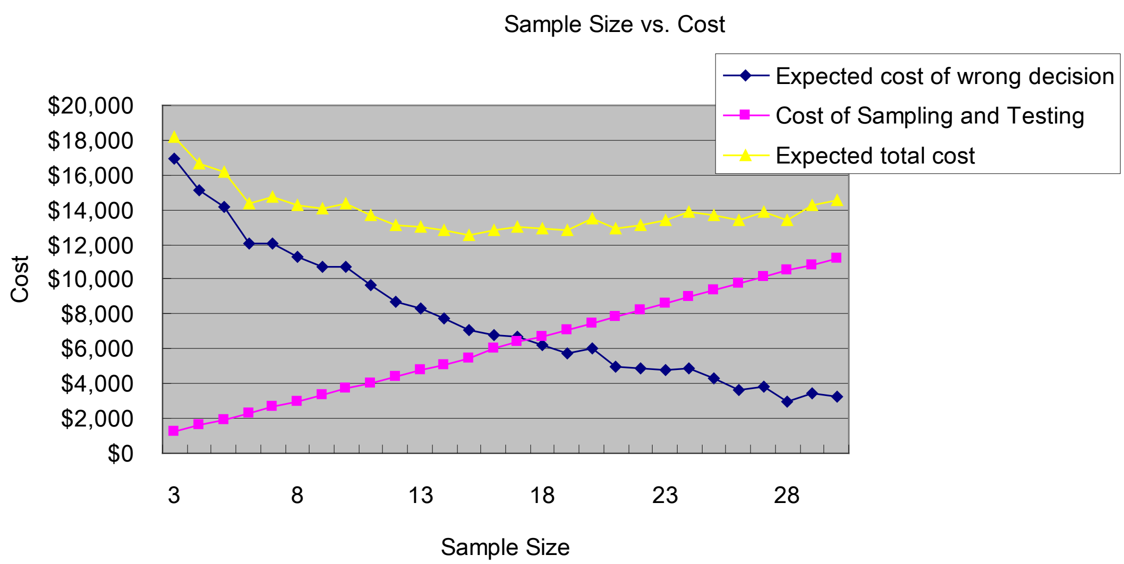


Figure 4-7. Independent Double AQCs model for Optimum Sample Size

4.2.3 Dependent Double AQCs

If multiple AQCs are correlated (i.e., dependent), cost equation is computed as follows:

$C_D = \sum (P_{r\ \text{each AQC\_given}} \times \beta_{\text{xx each AQC}}) \times \text{Unit Price} \times \text{Lot Size}$ …………14

Where,

$P_{r\ \text{each AQC\_given}}$ = proportion of prior lots of rejectable quality for AQC given the quality level proportions of other correlated AQCs

$\beta_{xx\ \text{each AQC}}$ = probability of accepting a lot having xx PWL for each AQC

Conditional probabilities from fictitious dada are used to make Venn diagram. The database shows that 0 percent of the air void lots are in RQL class, 50 percent are in AQL class, and 50 percent are 95 PWL class for AQC2 when asphalt binder content lots (AQC1) are in RQL class and 0 percent of the submitted asphalt binder content lots are in RQL class, 100 percent are in AQL class, and 0 percent are 95 PWL class when air void lots (AQC2) are in RQL class.

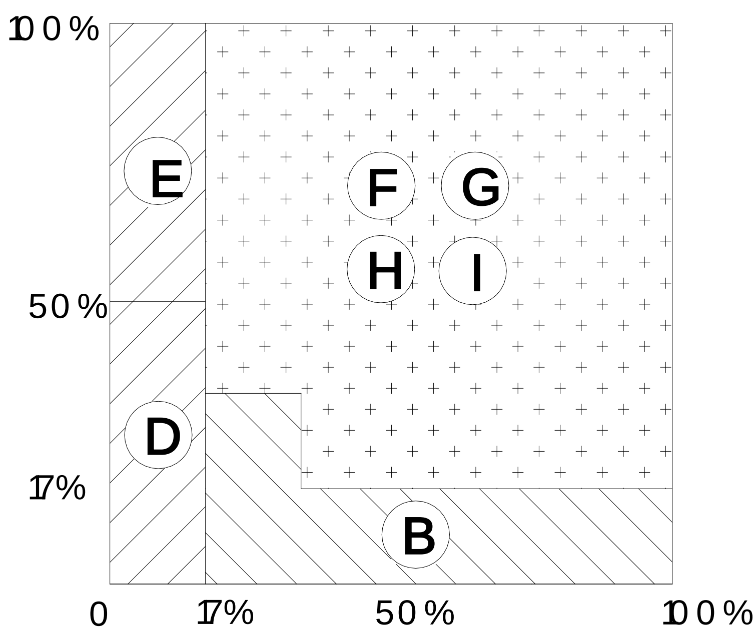


Figure 4-8. Venn Diagram for Dependent Double AQCs

Events A and C do not occur in fictitious data. Events F, G, H, and I are inconsequential to us. Acceptance decision error can not be made when neither AQC is RQL.

For this double AQC case, cost of making erroneous decisions is computed as follows:

$C_D = [(1/6)(1/2)\beta_{50}\beta_{90} + (1/6)(1/2)\beta_{50}\beta_{95} + (1/6)(1)\beta_{90}\beta_{50}] \times \text{Unit price} \times \text{Lot size}$ …15

As can be seen from Figure 4-9, optimum sample size n for independent double AQCs is 21. This size is larger than 15 for independent.

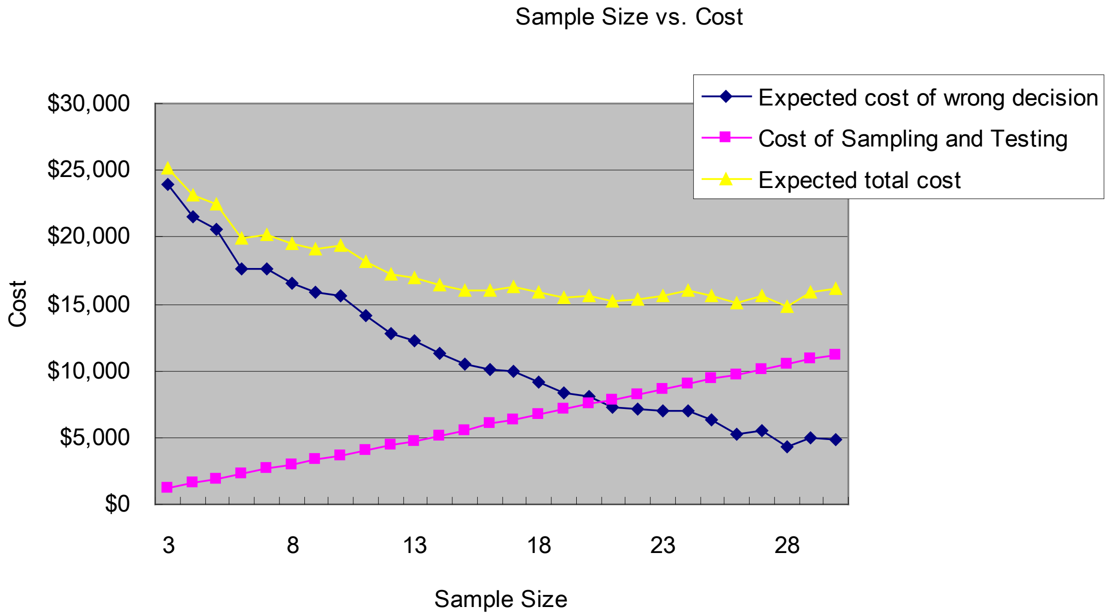


Figure 4-9. Dependent Double AQCs model for Optimum Sample Size

CHAPTER 5
5 DATA COLLECTION

5.1 Introduction

A data collection effort was required to obtain information necessary to apply the advanced optimization model that will allow determination of sample sizes for HMA concrete. For the collection of data, Colorado State Agency was selected because of following reasons. First its database was well organized lots of construction project data from as early as 2000. Second, it was the PWL base acceptance plan as Federal Highway Administration (FHWA) promoted to use PWL base. Third, it allowed additional research to better understand Quality Assurance issues. For example, a couple of AQCs were employed in current state highway construction to evaluate correlation between the multiple AQCs and determine the effect of having correlated versus uncorrelated AQCs on the determination of optimum sample size.

5.2 Colorado State Acceptance Plans

As a part of Colorado Department of Transportation's (CDOT) Standard Specifications for Road and Bridge Construction, subsection "Conformity to the Contract of Hot Mix Asphalt" governs the Quality Control (QC)/Quality Assurance (QA) calculations. Colorado State's hot mix asphalt gradation acceptance final report has asphalt content, gradation, in-place density, and joint density acceptance quality characteristics. This thesis was focused on the asphalt content and the in-place density characteristics with test sample sizes and pay factors (PF).

A few years ago, a standard provision revises or modifies CDOT's *Standard Specifications for Road and Bridge Construction*. That provision has gone through a formal review and approval process and has been issued by CDOT's Project their own quality of hot bituminous pavement. CDOT use this standard special provision on projects with 5000 or more metric tons (5000 or more tons) of hot bituminous pavement when acceptance is based on gradation, asphalt content and in-place density.

In this standard provision, sample size (n) in each process determines the final pay factor. PF is computed using the formulas designated in Table 5-1 (CDOT's own table). Appendix A describes PWL quality measure calculation.

Table 5-1 Formulas for calculating PF based on sample size

n (sample size)	Formulas for calculating PF	Maximum PF
3	$0.31177 + 1.57878\ (QL/100) - 0.84862\ (QL/100)^2$	1.025
4	$0.27890 + 1.51471\ (QL/100) - 0.73553\ (QL/100)^2$	1.030
5	$0.25529 + 1.48268\ (QL/100) - 0.67759\ (QL/100)^2$	1.030
6	$0.19468 + 1.56729\ (QL/100) - 0.70239\ (QL/100)^2$	1.035
7	$0.16709 + 1.58245\ (QL/100) - 0.68705\ (QL/100)^2$	1.035
8	$0.16394 + 1.55070\ (QL/100) - 0.65270\ (QL/100)^2$	1.040
9	$0.11412 + 1.63532\ (QL/100) - 0.68786\ (QL/100)^2$	1.040
10 to 11	$0.15344 +1.50104\ (QL/100) - 0.58896\ (QL/100)^2$	1.045
12 to 14	$0.07278 + 1.64285\ (QL/100) - 0.65033\ (QL/100)^2$	1.045
15 to 18	$0.07826 + 1.55649\ (QL/100) - 0.56616\ (QL/100)^2$	1.050
19 to 25	$0.09907 + 1.43088\ (QL/100) - 0.45550\ (QL/100)^2$	1.050
26 to 37	$0.07373 + 1.41851\ (QL/100) - 0.41777\ (QL/100)^2$	1.055
38 to 69	$0.10586 + 1.26473\ (QL/100) - 0.29660\ (QL/100)^2$	1.055
70 to 200	$0.21611 + 0.86111\ (QL/100)$	1.060
$\geq$ 201	$0.15221 + 0.92171\ (QL/100)$	1.060

If the PF is less than 0.75, the Engineer may:

1. Require complete removal and replacement with specification material at the Contractor's expense; or

2. Where the finished product is found to be capable of performing the intended purpose and the value of the finished product is not affected, permit the Contractor to leave the material in place.

CDOT uses weight factors in its composite pay equation. Table 3-2 shows the weights CDOT uses for four AQCs. Because only two of four CDOT's AQCs were analyzed in this thesis, weights in composite pay equation had to be adjusted.

Table 5-2 "W" Factors for Various Elements

HOT BITUMINOUS PAVEMENT	
ELEMENT	**W FACTOR**
Gradation	15
Asphalt Content	25
In-place Density	45
Joint Density	15

Since this thesis was focused on the asphalt contents and the in-place density, W factors were recalculated at 0.357 for asphalt content and 0.643 for density to be applied to data analysis.

CHAPTER 6

6 DATA ANALYSIS

6.1 Acceptance Quality Characteristics Data Analysis

6.1.1 Asphalt Content Data Analysis

CDOT's report for asphalt content has start date, grading, region number, project number, sample size, lot size, price per ton, quality level, pay factor, Incentive/Disincentive Payment (I/DP), standard deviation, etc. From this report, asphalt content data was resorted by sample sizes in 2000 year through 2007 year to check quality levels in actual practice. All data were classified by 25 classes (quality levels) and distribution of quality PWLs were calculated at each class shown in Table 6-1.

Table 6-1 Asphalt Content Proportion

Class (PWL)	Frequency Lot Numbers	Proportion (Percent)
0-4	1	0.16
4-8	0	0.00
8-12	0	0.00
12-16	0	0.00
16-20	0	0.00
20-24	2	0.32
24-28	0	0.00
28-32	1	0.16
32-36	2	0.32
36-40	1	0.16
40-44	3	0.48
44-48	4	0.65
48-52	7	1.13
52-56	7	1.13
56-60	7	1.13
60-64	8	1.29
64-68	13	2.10
68-72	21	3.39
72-76	20	3.23

Class (PWL)	Frequency Lot Numbers	Proportion (Percent)
76-80	29	4.68
80-84	40	6.45
84-88	56	9.03
88-92	65	10.48
92-96	93	15.00
96-100	240	38.71
Total	620	100.00

Table 6-1 Continued Asphalt Content Proportion

From analysis of CDOT database, at least 50 percent of lots were estimated to be better than AQL (about 85 PWL depending on pay equation). Based on the CDOT data and supported by discussions with FHWA official, there is sufficient reason to believe that most states have lot-quality distributions that are much better than the distribution Gharaibeh assumed for his “good” category. The CDOT database contains lots with n ranging from 3 to well over 100. The comparison consisted of grouping lots by sample size and comparing PWL estimates shown in Figure 6-1 and 6-2. (Kopac, 2010)

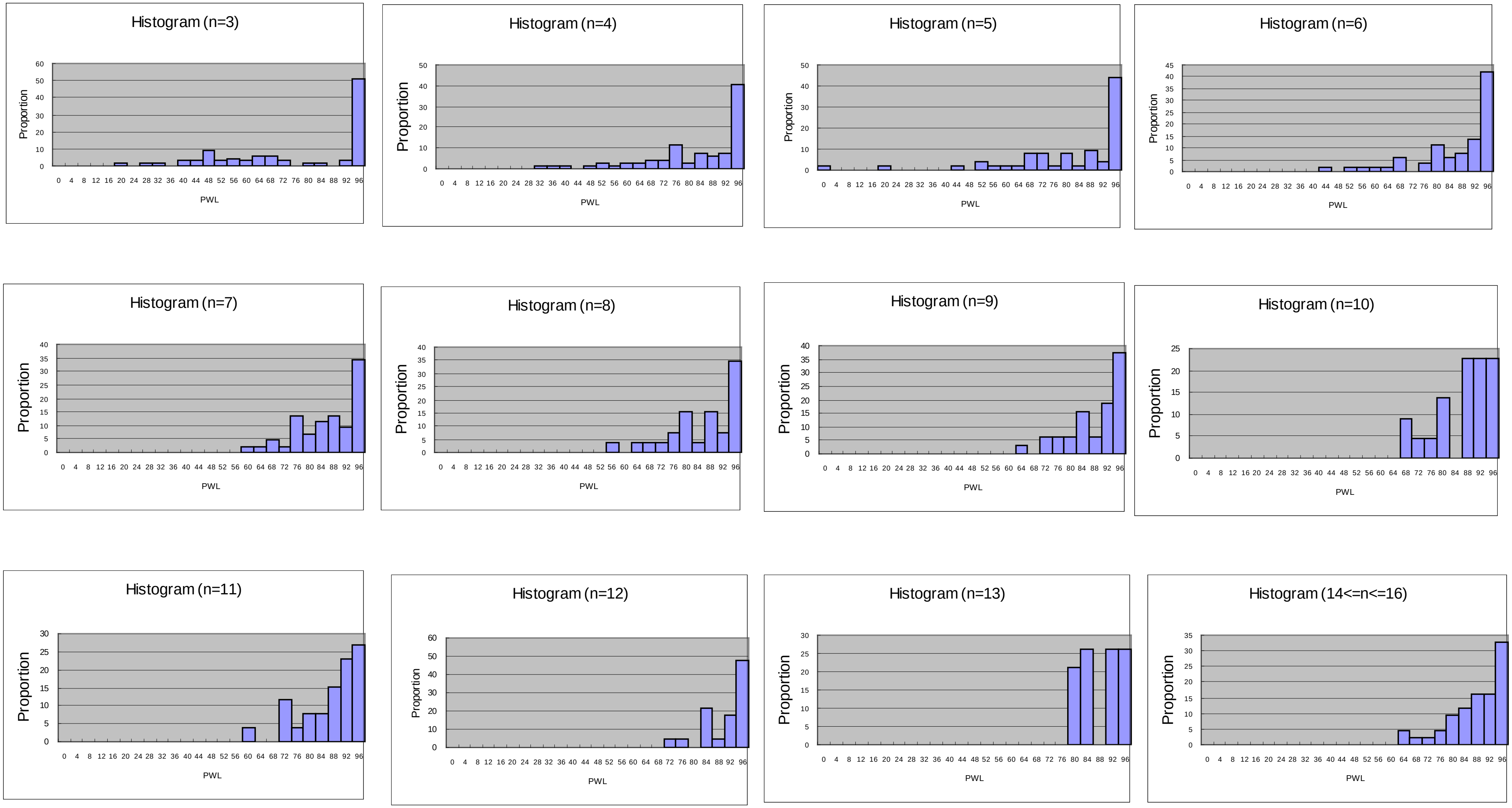


Figure 6-1. Proportion Histogram at each sample size category for Asphalt Contents I

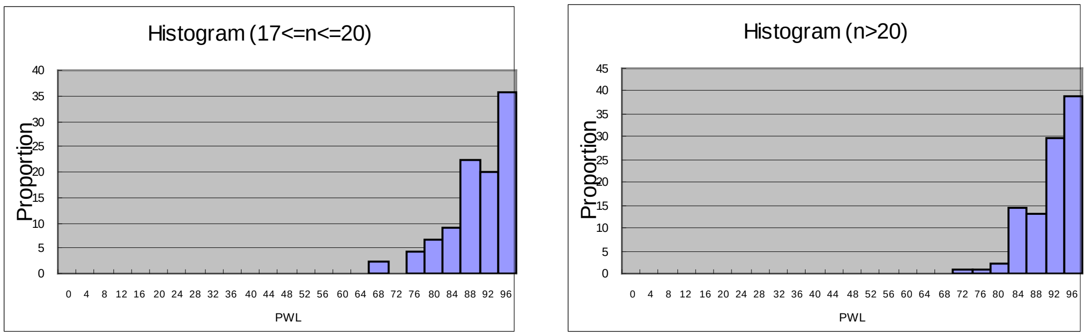


Figure 6-2. Proportion Histogram at each sample size category for Asphalt Contents II

As sample sizes decrease, the spread of PWL estimates increases; thus, the smaller *n* distributions contain not only more low-quality estimates but also more high-quality estimates. This does not mean that the true quality is different, only that the quality estimates have different distributions.

Figure 6-3 shows all data proportion versus quality level for asphalt contents. The 38.71 percent of lots range between 96 and 100 PWL.

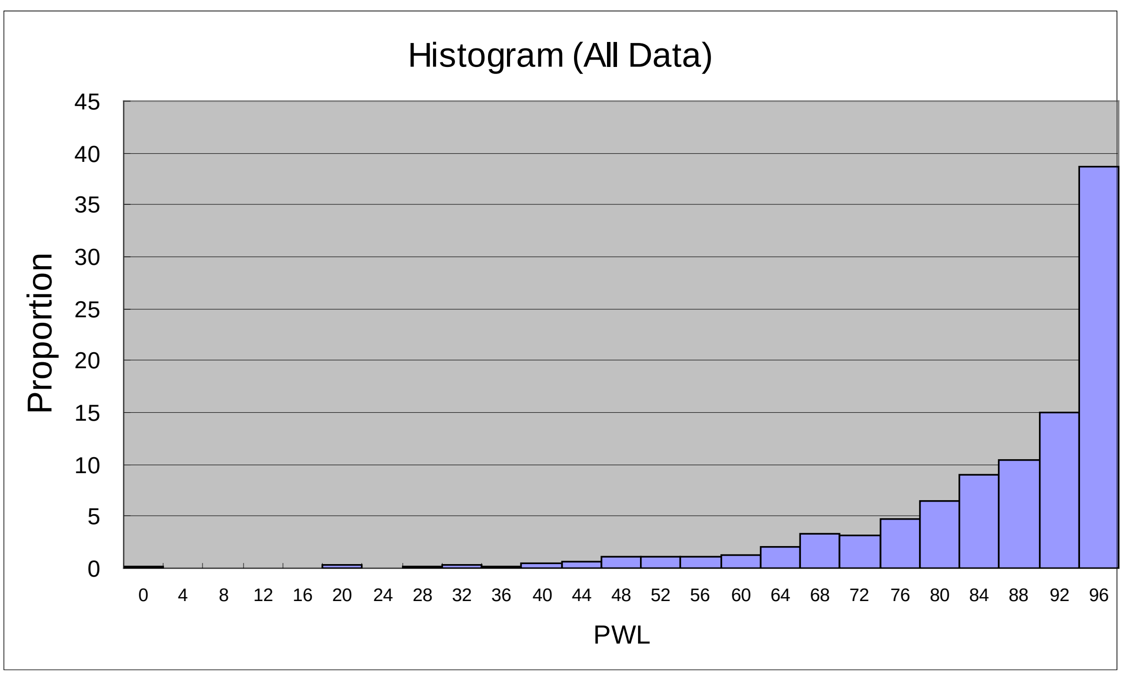


Figure 6-3. Proportion Histogram for Asphalt Contents

6.1.2 In-Place Density Data Analysis

From CDOT database, In-place density of asphalt data was also categorized by 25 quality levels in actual practice. The distribution of quality PWLs were calculated at each class shown in Table 6-2 and Figure 6-4.

Table 6-2 In-Place Density Proportion

Class (PWL)	Frequency (Lot Numbers)	Proportion (Percent)
0-4	0	0.00
4-8	0	0.00
8-12	0	0.00
12-16	0	0.00
16-20	0	0.00
20-24	0	0.00
24-28	0	0.00
28-32	0	0.00
32-36	2	0.33
36-40	1	0.16
40-44	0	0.00
44-48	0	0.00
48-52	1	0.16
52-56	2	0.33
56-60	4	0.65
60-64	4	0.65
64-68	5	0.82
68-72	10	1.64
72-76	13	2.13
76-80	28	4.58
80-84	37	6.06
84-88	53	8.67
88-92	86	14.08
92-96	111	18.17
96-100	254	41.57
Total	611	100.00

The distribution of In-Place density data had a similar tendency as the one of asphalt contents. The 82.49 percent of lots were estimated to be better than AQL (85 PWL).

The anticipated quality distribution of incoming lots is an important variable in determining optimum *n* since the highway agency is using its acceptance system to make acceptance decisions on all incoming lots, not just on a lot of a given quality level (not on a typical lot, for example). If incoming lots are anticipated to be generally high quality (i.e., good means, low standard deviations), less testing is needed. This is because the joint probability of a contractor delivering and the agency accepting a poor-quality lot is smaller when most incoming lots are of high quality; the expected cost of erroneous acceptance decisions is smaller for high-quality lots as shown in Figure 3-1 model.

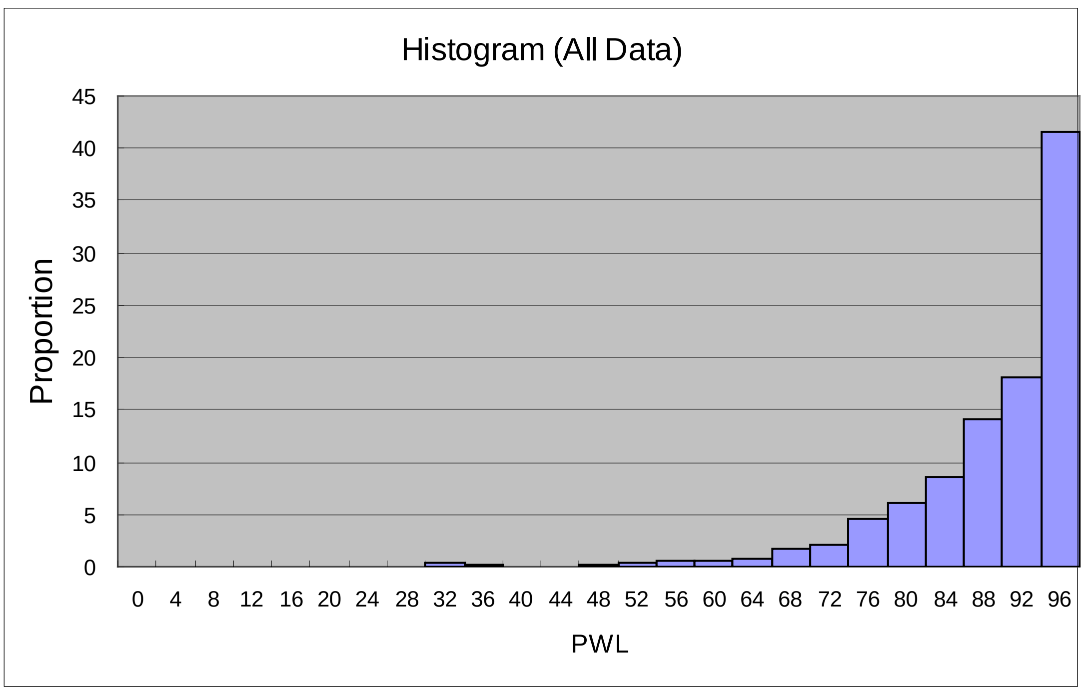


Figure 6-4. Proportion Histogram for In-Place Density

6.1.3 Multi Characteristics Analysis

It is important to understand that while an agency can apply the general model either a single AQC (a plan) or to multiple AQCs (a system of plans), true optimization can occur only when the agency applies it to the whole system rather than just to a component of the system. Most, if not all, highway agencies have multi-AQC systems. CDOT has also multi-AQCs such as asphalt contents, in-place density, gradation, joint density, etc. in the HMA. For this study, asphalt contents and in-place density AQCs were chosen to determine the required sample sizes to correspond to the desirable level of risk. These AQCs were also efficiency to explain correlation as a view of AQC lot quality measures (e.g., lot PWLs). Based on CDOT database, for these AQCs, only lots (528 lots) that had same mix design number were selected to concern muti-AQC system risks.

6.2 Correlation Between Two AQCs

In previous research, optimization model assumed AQCs were independent or weakly dependent. The assumption seemed logical considering highway agencies are generally discouraged from using correlated AQCs (Burati, 2005). Even when agencies do use correlated AQCs, contractors tend to pay attention to individual AQC quality rather than to combined measures of quality; if one AQC is poor-quality, it does not necessarily indicate other AQCs are also poor-quality (Gharaibeh, 2010).

In this study, the effect of correlated AQCs on optimum n was investigated. The study showed first, that for purposes of the optimization, the issue is not whether the AQC test results are correlated but whether the AQC lot quality measures (e.g., lot PWLs) are correlated. From the CDOT data, asphalt content and in-place density AQCs were organized with same physical lots and then used to determine the degree of correlation that might be expected between AQC lot PWLs, and the effect of AQC lot PWL correlation on optimum n.

The plot of density lot PWLs versus corresponding asphalt content lot PWLs were shown in Figure 6-5. Each data point represents a pair of PWLs that came from the same physical lot. In-Place density and asphalt content were sampled at different frequencies, but the average sample size (average n = 24 for density and average n = 13 for asphalt content) is large enough that the PWL estimates can be considered to be fair estimates of the population PWLs.

Figure 6-5 is typical of the plots one obtains with the various combinations of CDOT AQC lot PWLs. Data points are clustered at the upper right, indicating very high lot quality; and they also tend toward either axis, indicating a lack of correlation. Where R^2 is the correlation coefficient, y is the trendline of the correlation. Because conventional correlation techniques should not be used to determine the degree of correlation between non-normally distributed variables whose values contain testing error and are “top-heavy,” a procedure to calculate a new measure of correlation, the “relative correlation ratio,” was developed as an aside in this study specifically for use in determining the degree of correlation between AQC lot PWLs. This procedure compares the plot from actual PWL data (e.g., Figure 6-5) against a plot using the same PWL data but where the PWL pairs are assigned randomly, thus representing independence (i.e., Figure 6-6). Because data points are clustered at the upper right, one can count data points which are less or equal than 80 PWL. In figure 6-6, 21 data points were at less than 80 PWL, on the other hands, in Figure 6-6, 9 data points were counted for both 2 figures. The relative correlation ratio was developed as 2.333 (21/9) for both cases. As this ratio is closer to 1, one can say two AQC lots are more strongly correlated.

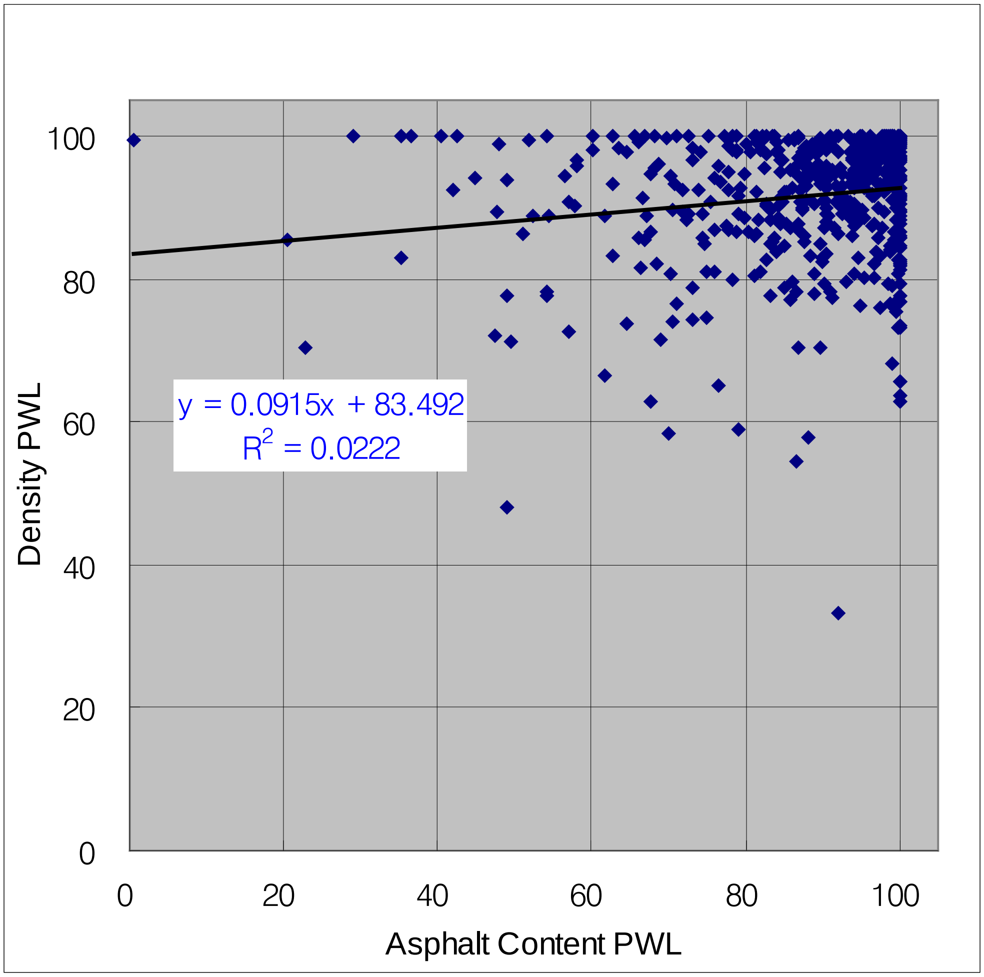
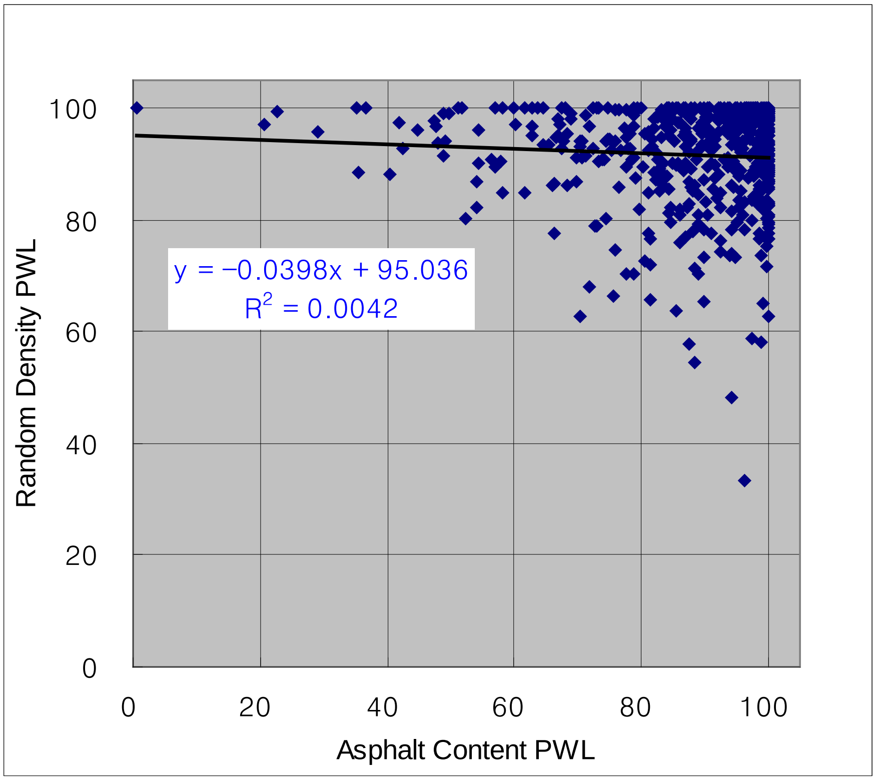


Figure 6-5. Plot of Density and Asphalt Content Lot PWL Pairs



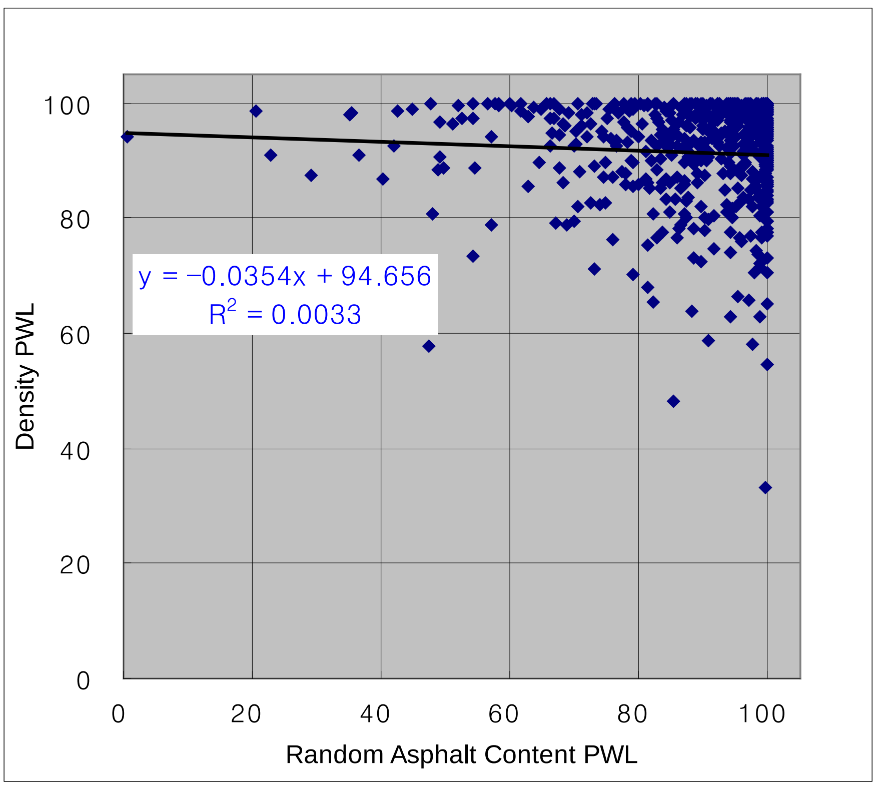


Figure 6-6. Plots of Randomly Assigned Density and Asphalt Content Lot PWL Pairs

The degree of correlation was found to have a negligible effect on the total optimum n. For the degree of correlation in Figure 6-5 (where the plot exhibited mild correlation using the relative correlation ratio), the optimization procedure arrived at the same optimum n = 3 for each AQC (total n = 6) as that arrived under an assumption of independence. Even if the density and asphalt content lot PWLs were strongly correlated, the optimization procedure still arrives at an optimum n = 3 for each AQC. However, according to the optimization procedure (and logic), if the total optimum n for two perfectly correlated AQCs is 6, the lowest cost to the agency occurs when n = 6 for the AQC having the lower sampling and testing and n = 0 for the AQC having the higher sampling and testing cost. Thus, unless the agency "needs" to use both AQCs, as it might when each AQC controls different key distresses, the recommended course of action to achieve optimization is for the agency to drop the higher cost AQC from its acceptance system. The optimization procedure thus provides an economic argument against the use of highly correlated AQCs.

6.3 Pay Adjustments

The theory behind acceptance plan development that was initially presented to the highway community in the 60's dealt strictly with accept/reject acceptance plans (Military Standard 414, 1957, Development of Guidelines for Practical and Realistic Construction Specifications, 1967). In the intervening years, the theory had to be expanded as state highway agencies adopted first pay decreases (penalties) then also pay increases (bonuses) associated with different levels of estimated quality. Although the vast majority of acceptance plan systems now contain pay adjustment provisions, there are still gaps in our understanding of pay adjustment development and function.

In the previous research, Gharaibeh assumed that the cost consequences of erroneous pay decisions were such that, in the long run, the positive cost consequences incurred when the agency underestimates quality and pays less than it should cancel out the negative cost consequences incurred when it overestimates quality and pays more than it should; in other words, he essentially treated pay-adjustment acceptance plans as if they were accept/reject acceptance plans.

6.3.1 CDOT Data with Agency's Desired Pay Factor

To calculate the cost of erroneous pay decisions in the this study, it was assumed that the agency's desired pay factor for a lot having any combination of AQC PWLs is, by definition, whatever the agency wants it to be for that particular AQC PWL combination. Obviously, what the agency wants it to be is spelled out in the agency pay equations. The CDOT pay equations (which are a function of sample size, see Table 5-1) were thus used to determine the agency's desired multi-AQC pay. The SpecRisk software program was used to determine the contractor's multi-AQC expected pay. The difference between the contractor's expected pay and the agency's desired pay is the cost of erroneous pay decisions. Table 6-3 shows classified AQCs PWL CDOT data with pay factors. The agency's desired multi-AQC pay factor is calculated in Table 6-4.

Table 6-3 Classified AQCs PWL Data with Pay Factor

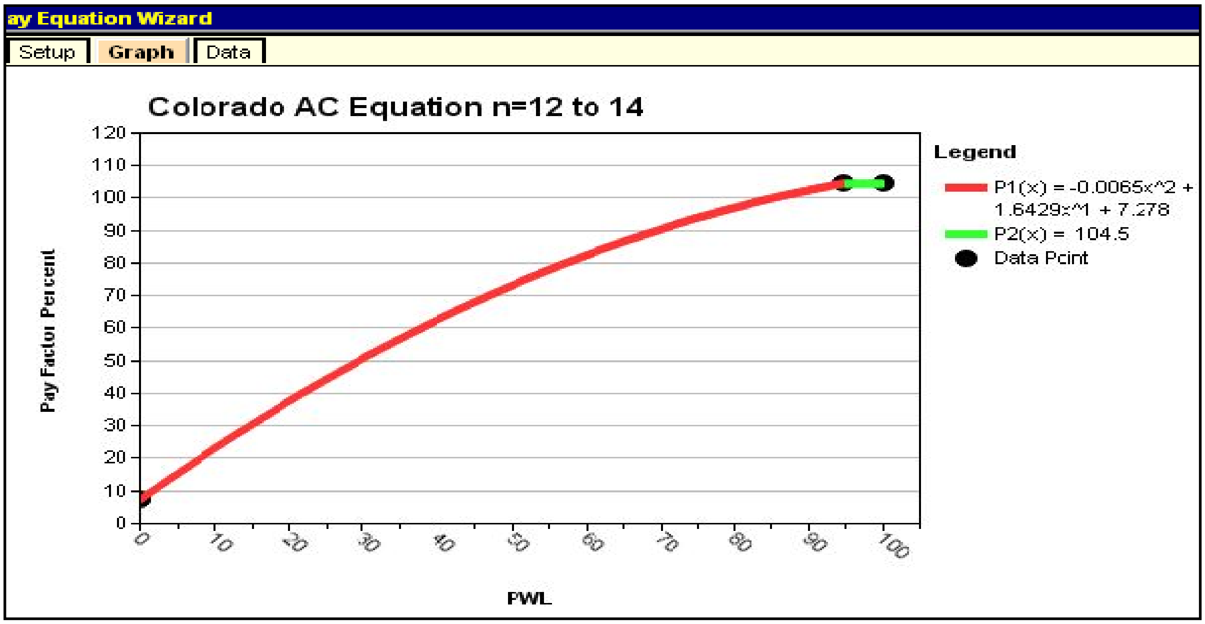
Class	Representative PWL	AC. Proportion		Den. Proportion		Pay Factor (n=12~14), 1.045	Pay Factor (n=15~18), 1.050	Pay Factor (n=19~25), 1.050	Pay Factor (n=3), 1.025
Class 1	30 PWL	0-45 PWL	2.08%	0-45 PWL	0.19%	0.50711	0.49425	0.48734	0.70903
Class 2	58 PWL	45-65 PWL	5.68%	45-65 PWL	1.70%	0.80686	0.79057	0.77575	0.94199
Class 3	75 PWL	65-80 PWL	12.88%	65-80 PWL	8.52%	0.93911	0.92716	0.91601	1.01851
Class 4	87 PWL	80-90 PWL	20.83%	80-90 PWL	22.92%	1.00982	1.00388	0.99917	1.04299
Class 5	97 PWL	90-100 PWL	58.52%	90-100 PWL	66.67%	1.05445	1.05536	1.05844	1.04472

Table 6-4 Agency's Desired Pay Factor for A Lot Having any Combination of AQC PWLs

Possible Events	Desired Pay Decision						
	reject or pay	PF, n=3	Maximum PF (1.025)	PF, n=15~18	Maximum PF (1.050)	Combined PF (AQC1:n=12~14, AQC2:n=19~25)	Maximum PF (1.048215)
AQC1 in class 1 and AQC2 in class 1	reject or pay	0.70903	0.70903	0.49425	0.49425	0.49440	0.49440
AQC1 in class 1 and AQC2 in class 2	reject or pay	0.85882	0.85882	0.68478	0.68478	0.67984	0.67984
AQC1 in class 1 and AQC2 in class 3	reject or pay	0.90802	0.90802	0.77261	0.77261	0.77003	0.77003
AQC1 in class 1 and AQC2 in class 4	reject or pay	0.92376	0.92376	0.82194	0.82194	0.82350	0.82350
AQC1 in class 1 and AQC2 in class 5	reject or pay	0.92488	0.92488	0.85504	0.85504	0.86162	0.86162
AQC1 in class 2 and AQC2 in class 1	reject or pay	0.79219	0.79219	0.60004	0.60004	0.60141	0.60141
AQC1 in class 2 and AQC2 in class 2	pay	0.94199	0.94199	0.79057	0.79057	0.78686	0.78686
AQC1 in class 2 and AQC2 in class 3	pay	0.99119	0.99119	0.87840	0.87840	0.87704	0.87704
AQC1 in class 2 and AQC2 in class 4	pay	1.00693	1.00693	0.92773	0.92773	0.93051	0.93051
AQC1 in class 2 and AQC2 in class 5	pay	1.00804	1.00804	0.96083	0.96083	0.96863	0.96863
AQC1 in class 3 and AQC2 in class 1	reject or pay	0.81951	0.81951	0.64880	0.64880	0.64862	0.64862
AQC1 in class 3 and AQC2 in class 2	pay	0.96930	0.96930	0.83933	0.83933	0.83407	0.83407
AQC1 in class 3 and AQC2 in class 3	pay	1.01851	1.01851	0.92716	0.92716	0.92426	0.92426
AQC1 in class 3 and AQC2 in class 4	pay	1.03425	1.02500	0.97649	0.97649	0.97773	0.97773
AQC1 in class 3 and AQC2 in class 5	pay	1.03536	1.02500	1.00959	1.00959	1.01584	1.01584
AQC1 in class 4 and AQC2 in class 1	reject or pay	0.82825	0.82825	0.67619	0.67619	0.67387	0.67387
AQC1 in class 4 and AQC2 in class 2	pay	0.97804	0.97804	0.86672	0.86672	0.85931	0.85931
AQC1 in class 4 and AQC2 in class 3	pay	1.02725	1.02500	0.95455	0.95455	0.94950	0.94950
AQC1 in class 4 and AQC2 in class 4	pay	1.04299	1.02500	1.00388	1.00388	1.00297	1.00297
AQC1 in class 4 and AQC2 in class 5	pay	1.04410	1.02500	1.03698	1.03698	1.04109	1.04109
AQC1 in class 5 and AQC2 in class 1	reject or pay	0.82887	0.82887	0.69457	0.69457	0.68980	0.68980
AQC1 in class 5 and AQC2 in class 2	pay	0.97866	0.97866	0.88510	0.88510	0.87525	0.87525
AQC1 in class 5 and AQC2 in class 3	pay	1.02786	1.02500	0.97293	0.97293	0.96543	0.96543
AQC1 in class 5 and AQC2 in class 4	pay	1.04361	1.02500	1.02226	1.02226	1.01890	1.01890
AQC1 in class 5 and AQC2 in class 5	pay	1.04472	1.02500	1.05536	1.05000	1.05702	1.04822

6.3.2 Contractor's Expected Pay Factor

The SpecRisk software program was used to determine the contractor's multi-AQC expected pay. Figure 6-7 shows pay equation curves for asphalt content and in –place density as graphical input values.



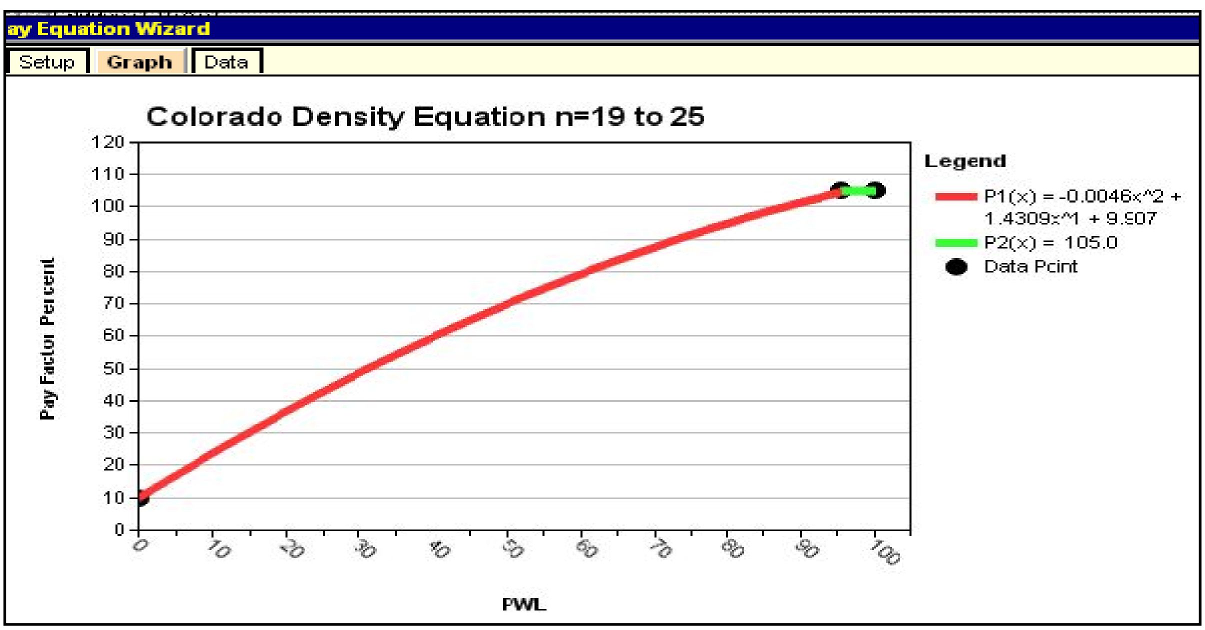
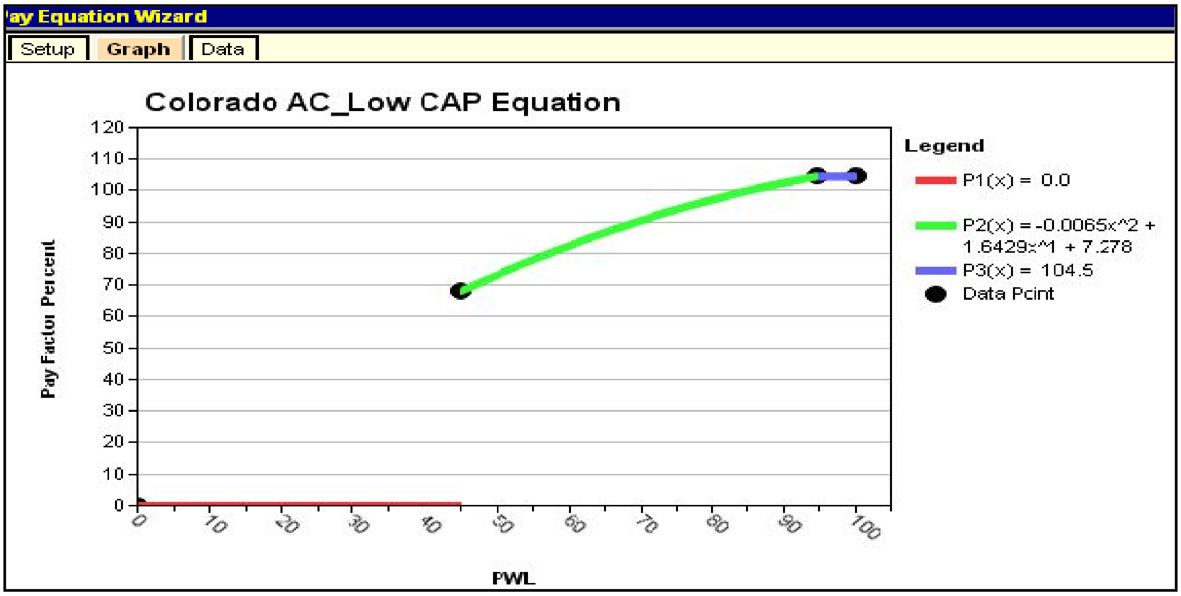


Figure 6-7. Pay Equation Curves for Asphalt Content and Density in SpecRisk software



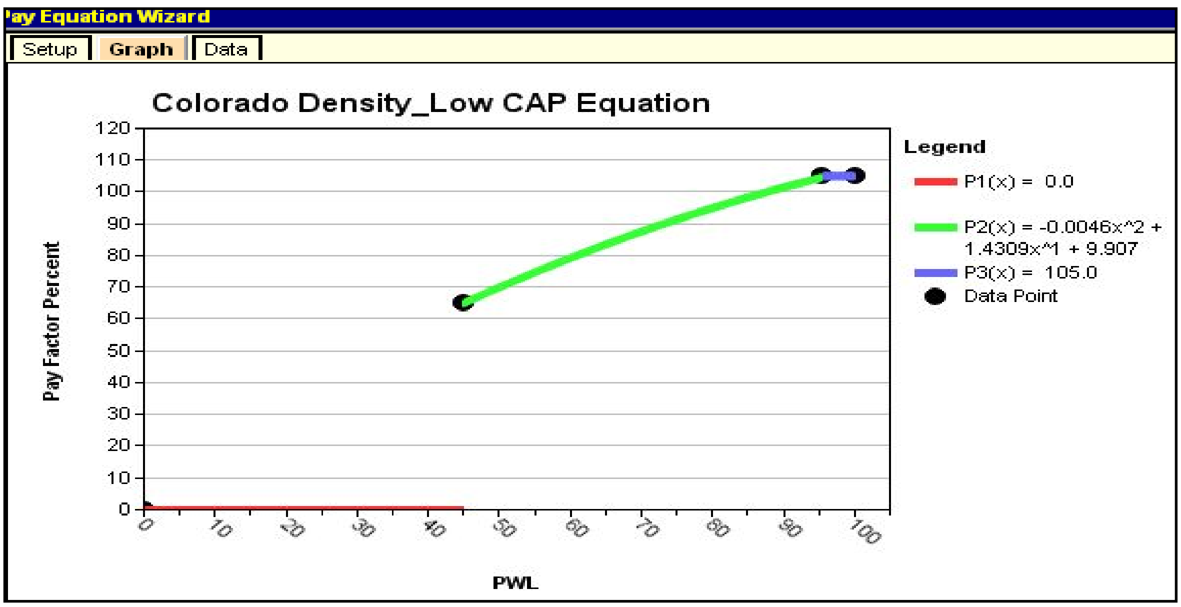


Figure 6-8. Pay Equation Curves for Asphalt Content and Density with a low threshold

To compare the estimated PWL pay curve and the expected pay curve, pay equation curve with low thresholds were considered shown in Figure 6-8. These pay curves both have a minimum acceptable estimated quality level of 45 PWL.

6.3.3 Pay Adjustment Acceptance Plan

In this study, the previous assumption (Gharaibeh, 2010) of zero cost of erroneous pay decisions was found to be incorrect as is shown in Table 6-5.

Table 6-5 Difference Between Agency's Desired Pay and Contractor's Expected Pay for n=3

Colorado A.C PWL	Colorado Den. PWL	Expected Pay	Desired Pay	Difference between E.P and D.P
30	30	0.46375	0.49440	-0.03065
30	58	0.63796	0.67984	-0.04189
30	75	0.74035	0.77003	-0.02968
30	87	0.80059	0.82350	-0.02291
30	97	0.83396	0.86162	-0.02765
58	30	0.56520	0.60141	-0.03621
58	58	0.74728	0.78686	-0.03958
58	75	0.84679	0.87704	-0.03026
58	87	0.89846	0.93051	-0.03206
58	97	0.94456	0.96863	-0.02407
75	30	0.61977	0.64862	-0.02885
75	58	0.80878	0.83407	-0.02529
75	75	0.89234	0.92426	-0.03192
75	87	0.94434	0.97773	-0.03338
75	97	0.98748	1.01584	-0.02836
87	30	0.64651	0.67387	-0.02736
87	58	0.82445	0.85931	-0.03486
87	75	0.91494	0.94950	-0.03456
87	87	0.97156	1.00297	-0.03141
87	97	1.01572	1.04109	-0.02537
97	30	0.66922	0.68980	-0.02058
97	58	0.84108	0.87525	-0.03416
97	75	0.93830	0.96543	-0.02714
97	87	0.99119	1.01890	-0.02772
97	97	1.03339	1.04822	-0.01483

As pay adjustment acceptance plans were not designed to make erroneous pay decision cost consequences cancel each other, it would be coincidental for that to happen.

This study showed that the net consequences of erroneous pay decisions not only could be considerable, but that they tended to favor the highway agency, i.e., to underpay contractors. When the agency uses an acceptance plan system that in the long run underpays contractors, the agency's expected cost of erroneous acceptance decision (hence, the agency's total cost of lot acceptance) is decreased.

Figure 6-9 and 6-10, developed from CDOT data, can be used as examples to illustrate such a situation. In Figure 6-9, the expected cost of erroneous acceptance decisions is negative throughout the range of *n*; the smaller the *n*, the greater the probability of erroneous acceptance decisions, thus the more negative the expected cost, i.e., the more the contractor is underpaid. These negative costs bring the optimization model's "total cost of lot acceptance" curve below the "cost of sampling and testing" curve. With respect to optimum *n*, it is *n* = 3, which is the lowest possible *n* for the PWL quality measure.

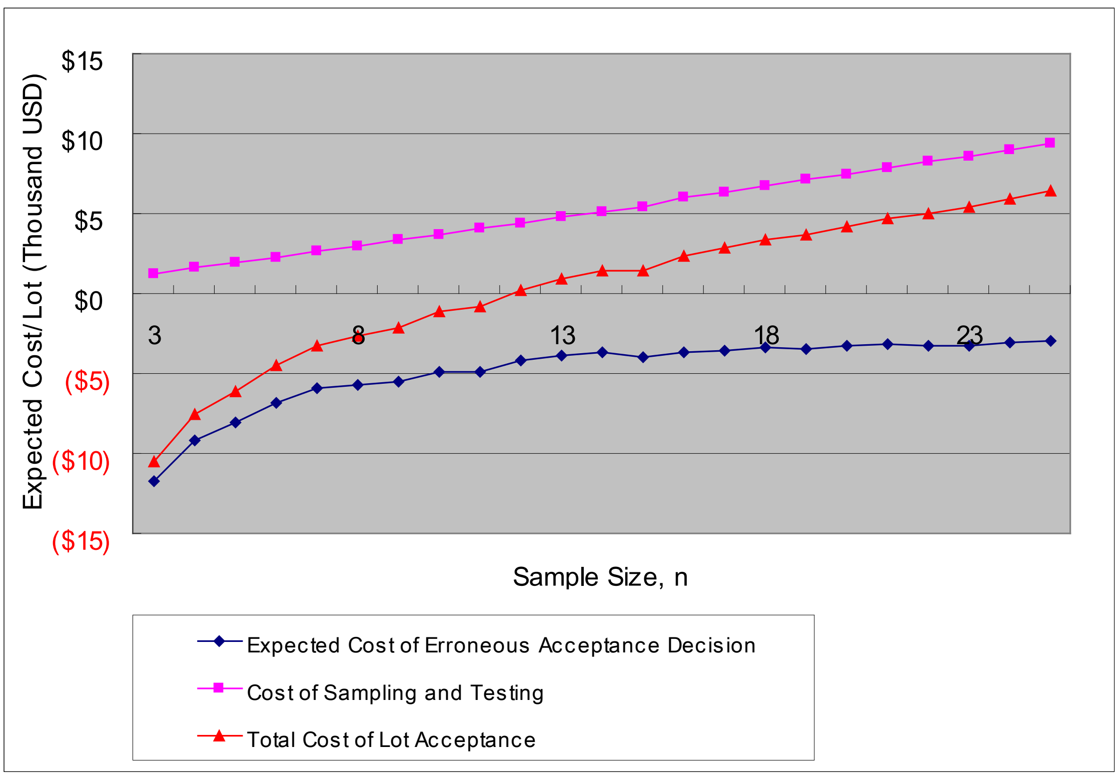


Figure 6-9. Application of optimization model with negative agency acceptance costs

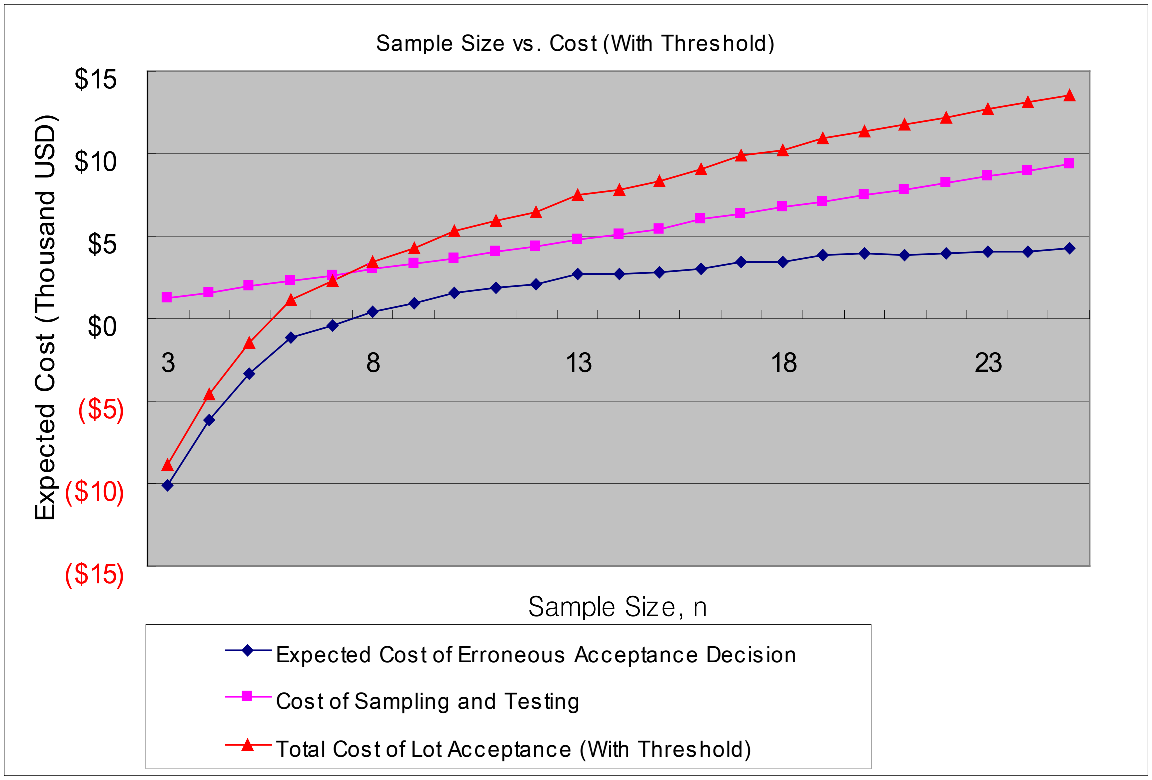


Figure 6-10. Application of optimization model with negative agency acceptance costs (with Threshold)

Two variables come into play for the situation depicted in Figure 6-9 and 6-10 to occur—the lot-quality distribution and the pay adjustment provisions. Figure 6-11 can provide a better understanding. It compares the composite pay equation with its expected pay curve for a two-AQC acceptance system (with the X-axis identifying the same PWL for both AQCs (Asphalt Contents and In-Place Density)). Note that the composite pay equation has both a minimum acceptable estimated quality level (45 PWL) and a maximum pay factor cap (102.50 PWL). When the lot-quality distribution is such that delivered lots rarely fall below 45 PWL, the portion of the graph to the right of 45 PWL carries a much greater weight. One can thus see that under such conditions, unless one or two specific contractors are consistently delivering the few instances of below 45 PWL lots, contractors as a whole are in the long run underpaid in comparison to agency-desired pay.

Of the two variables, the lot-quality distribution appears to be the most influential. Application of the optimization model shows that the better the lot-quality distribution, the greater the likelihood of negative costs and associated long-run underpayment to the contractors. Further, the lot-quality levels need not be all that high for the long-run underpayment to occur. It can occur with Gharaibeh's “regular” and “good” historical quality distribution, whether or not the pay provisions include a maximum pay cap and/or a minimum acceptable estimated quality level (below which lots may be rejected), although use of the latter decreases the long-run underpayment.

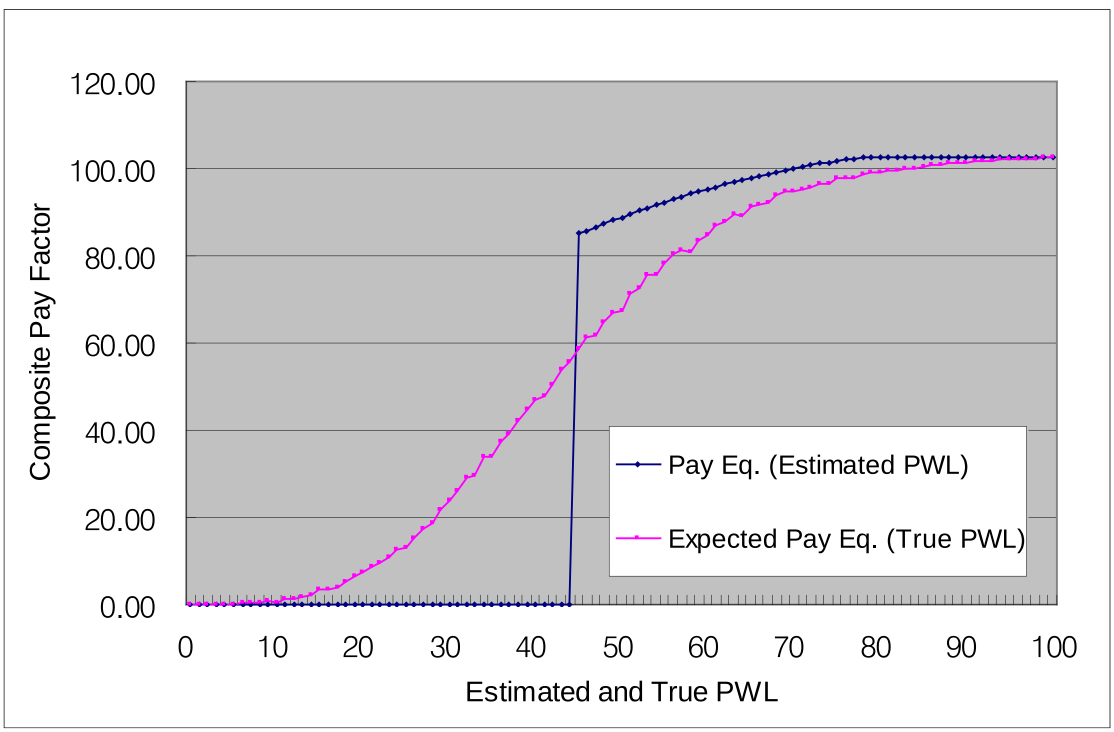


Figure 6-11. Comparison of a composite pay equation and its expected pay curve

It is also important to note that sample size is not causing the underpayment. Sample size simply affects the risks associated with contractor being assessed the correct payment. For high-quality lots, the risk of an occasional incorrect, low-quality estimate is greater with small sample sizes, thus resulting in the pay equation bias that leads to a greater expected underpayment. The underpayment should not be an issue, provided the agency has developed, is satisfied with, and has made available to contractors, the expected pay equation.

6.4 Cost of Sampling and Testing

The cost of sampling and testing is difficult to model because there are many different possible cost scenarios: a technician could perform two or more AQC tests simultaneously; a technician could perform another function while waiting for test results; one sample could yield several AQC test results; multiple technicians could be employed and be more (or less) efficient than a single technician; etc. In this study, a linear relationship (Gharaibeh, 2010) between the cost of sampling and testing and sample size *n* was used. This example explains how Figures 6-12 and 6-13 were developed based on the cost assumptions presented earlier. The cost of sampling and testing of 5 HMA cores for density is computed as follows:

Transportation between lab and project site $115.1

Coring ($99.6/core)..$498.1

Max. Theoretical Specific Gravity test ($52.3/core) $261.5

Density test ($26.2/core)..$130.8

Total (for 5 cores) $1,005.5

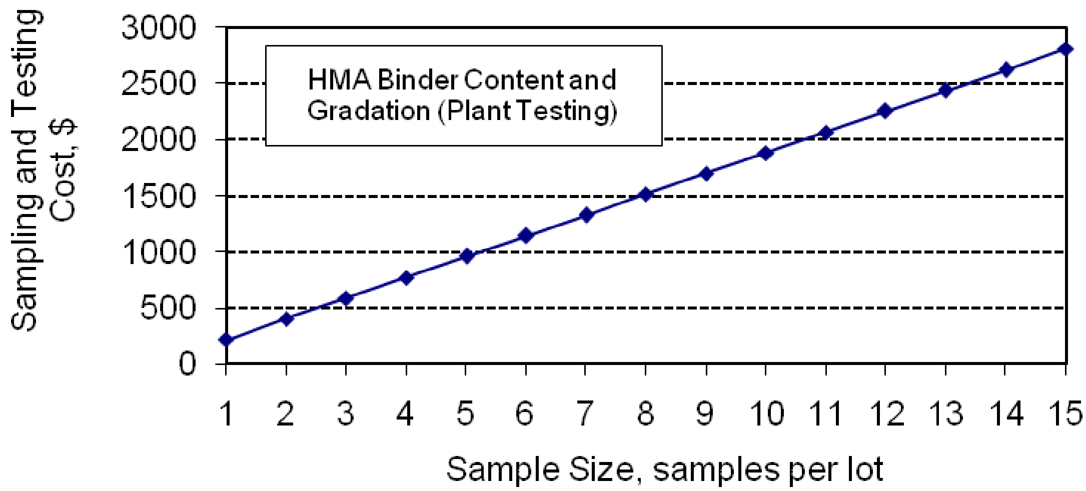


Figure 6-12. National Average Cost of Sampling and Testing for unmolded HMA (Binder Content and Gradation together) (2008 Prices)

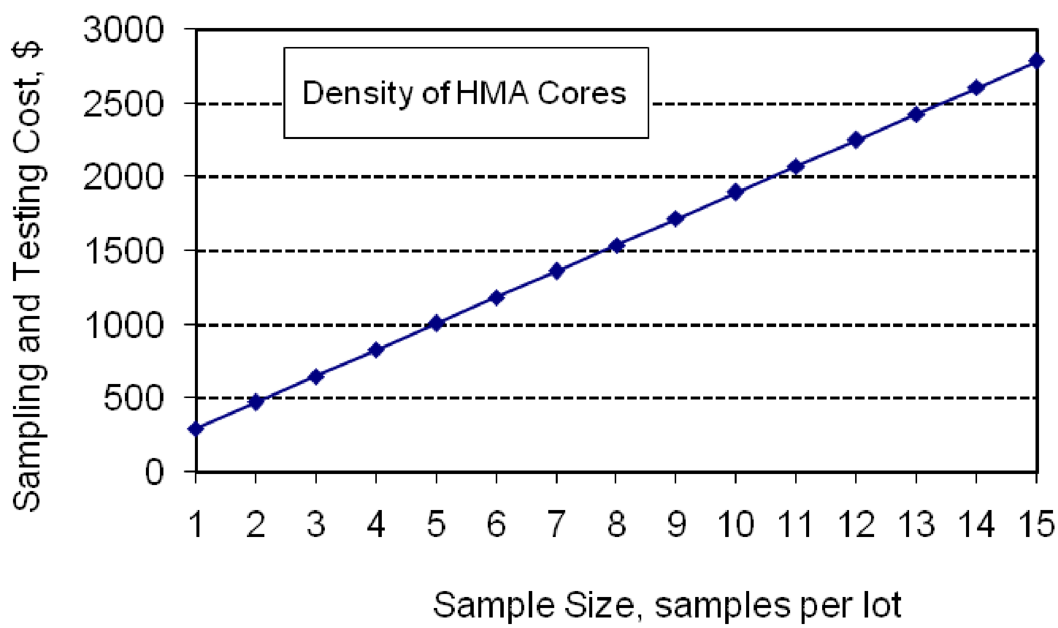


Figure 6-13. National Average Cost of Sampling and Testing for HMA Density Cores (2008 Prices)

As these examples, If a single assumption has to be made about the cost of sampling and testing element in a generalized optimization model, it would be hard to argue that linearity should not be the assumption.

The assumption of linearity tends to “average” all the possible cost scenarios that exist within the state and/or within the acceptance plan system. However, if an agency believes the cost of sampling and testing element to be other than linear for its optimization purposes, the agency can substitute its own specific model in performing the necessary calculations.

In any case, agencies should also consider stepped functions. A stepped cost of sampling and testing function is appropriate in a situation where the cost of performing additional tests is viewed as negligible up to a certain n, at which point it suddenly increases (Kopac, 2010). One such example is the cost of nuclear density testing. Under certain situations, the cost of nuclear density testing could stay about the same whether say, 3 tests or 10 tests, are performed in one day or by one technician. The cost could then noticeably increase if n = 11 tests required two technicians or extended the time on the job for one technician from say, 1 day to 2 days. With a stepped function, the best optimization solution is for the agency to accept n = 10 as the optimum in this example rather than the calculated n = 3.

Another assumption made by Gharaibeh dealt with the unit costs of sampling and testing. As indicated earlier, the higher the unit costs, the larger the optimum n. The unit costs Gharaibeh used represent national averages and are deemed to be sufficiently conservative. In this study, unit bid price was calculated by only CDOT data. State highway agencies that suspect their unit costs are higher can easily input their own costs.

6.5 Post-Construction Costs

Previous optimization modeling (Gharaibeh, 2010) assumed the agency's expected cost due to erroneous acceptance decisions is based solely on bid price and not any other costs such as user costs or maintenance and rehabilitation costs. This assumption may be valid for accept/reject acceptance plan systems for which there is a clear line between rejectable and acceptable lots and no need to distinguish among various levels of acceptable quality. This assumption, however, has no place in pay adjustment acceptance plan systems.

In this study, optimization modeling by its nature distinguishes among various levels of acceptable quality (and also among various levels of unacceptable quality). It indirectly considers user costs and maintenance and rehabilitation costs. These post-construction costs relate to the expected underpayment/overpayment to contractors as a result of erroneous pay decisions.

As stated earlier, this study found that the high-quality (above AQL) lots typically delivered to state highway agencies along with the caps placed on the maximum pay factor are responsible for the long-run underpayment to the contractors. Including user costs and maintenance and rehabilitation costs in the modeling significantly raises the performance-related pay increase the contractor “deserves” to have for above AQL lots. PaveSpec performance-related specifications (PRS) software shows that the inclusion of post-construction costs, even when using only 5 percent of the theoretical user cost, can result in very high “deserved” pay factors (FHWA-RD-00-131, 2000). That is partly why 100 percent of user costs is not used in PRS development, and why a cap is placed on the maximum PRS pay factor (Kopac, 2010). Both have the effect of underpaying the contractors, i.e., of creating negative costs to the agency that in turn decrease the calculated optimum *n* (below that optimum *n* calculated without post-construction costs).

6.6 Cost of Contractor Reaction

This study considered a third cost element separate from the two elements (Expected Cost of Erroneous Acceptance Decision and Cost of Sampling and Testing) identified in Figure 3-1. It addressed the impact on lot quality and cost if an agency switches to a smaller n than the one it currently uses.

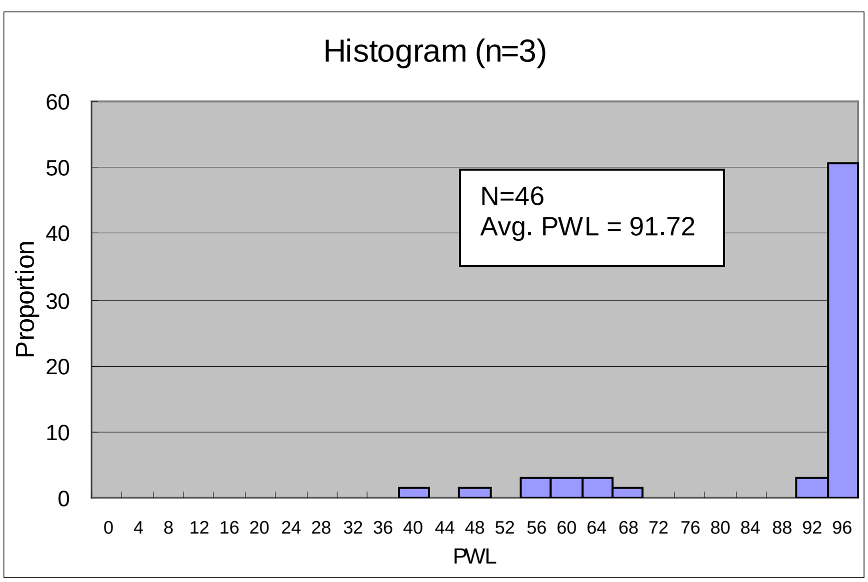
Preliminary indications are that with proper precautions there should be little if any difference in delivered (and accepted) quality. Contractors have already delivered many lots to various state highway agencies knowing that the acceptance sample size will be as small as n = 3 or 4 (Kopac, 2010).

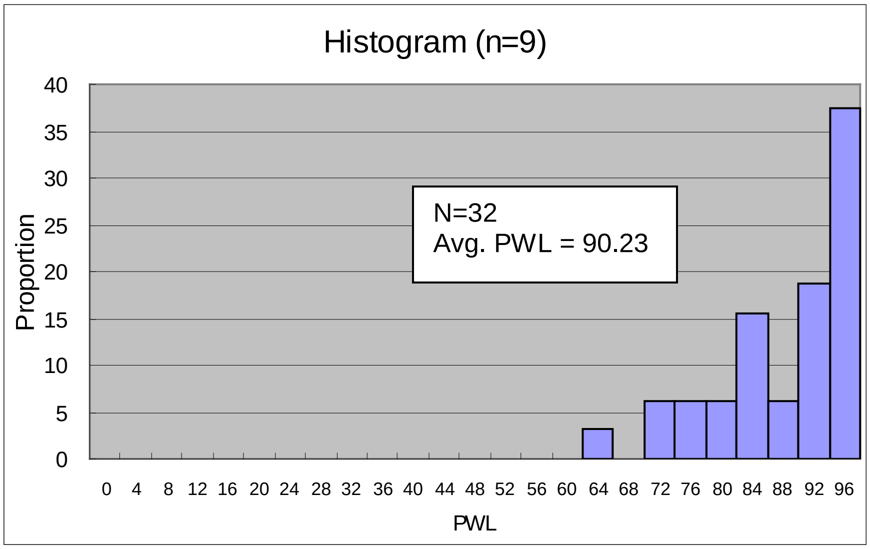
CDOT's database was used to make a comparison of hot mix asphalt quality delivered when the contractor knows n will be small. The CDOT data base contains lots with n ranging from 3 to well over 100. The comparison consisted of grouping lots by sample size and comparing PWL estimates. To allow a fair comparison, those lots that were meant to have higher n but had been prematurely discontinued due to unscheduled mix design changes were eliminated from the data.

An example comparison, using the n = 3, 9, and 17-20 groups, is shown in Figure 6-14. As one would expect, the spread of PWL estimates decreases as n increases; thus, the smaller n distributions contain not only more low-quality estimates but also more high-quality estimates. This does not mean that the true quality is different, only that the quality estimates have different distributions. The average PWL of the distribution is the best measure of true quality in this case, and the three average PWLs are about the same—91.72, 90.23, and 91.87 for n =3, 9, and 17-20 respectively. The nonparametric Mann-Whitney U test shows no difference among the three population means at α = .05 significance level.

An argument can even be made that, for some AQCs, quality increases with decreased *n*. A frequently cited example involves concrete compressive strength under an acceptance plan that uses the average as the quality measure (Kopac, 2010). With smaller *n*, a contractor would need to target a higher average compressive strength in order to meet the minimum average estimated strength requirement with the same probability as for larger *n*. This argument holds not only for compressive strength but also other one-sided AQCs such as thickness, density and smoothness; and other quality measures such as PWL.

In Figure 6-14, it is the spread of the distributions (the error associated with the estimated PWLs) that would motivate a contractor to increase quality for either one-sided or two-sided AQCs. For two-sided AQCs, rather than increasing (improving) the lot average, the contractor would want to decrease variability. Either way, the contractor's costs theoretically would increase, but the post construction costs would probably decrease.





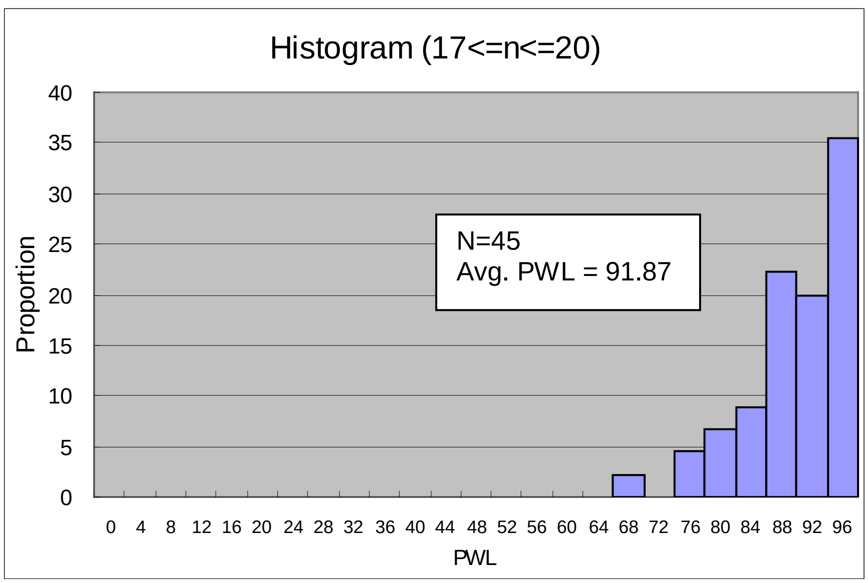


Figure 6-14. Distribution of CDOT asphalt content PWL estimates for lots with n=3, 9, and 17-20

CHAPTER 7

7 CONCLUSIONS RECOMMENDATIONS

7.1 Summary and Conclusions

This study concluded that previous optimization model (Gharaibeh, 2010) assumptions were indeed conservative. With modified assumptions, based where possible on actual data, the optimum acceptance sample size *n* is even smaller than that calculated by Gharaibeh. However sample size *n* cannot be less than 3 for PWL acceptance plans as PWL estimates cannot be made with less than 3 test results.

For acceptance plan systems related to pavements, optimum *n* is primarily a function of incoming lot quality—the higher the quality the lower the *n*. To illustrate with an extreme example, if an agency was certain that incoming lots will be of such high quality that none should be rejected, there would be no need for the agency to do any testing under an accept/reject acceptance system. The term “acceptance system” however, has become somewhat of a misnomer. For many highway agencies, it is more a “pay adjustment system,” i.e., more for the purpose of making pay adjustment decisions rather than accept/reject decisions. This study examined pay adjustment acceptance systems and concluded for them too, optimum *n* is primarily a function of incoming lot quality. When incoming lot quality is anticipated to be high, the expected cost associated with erroneous pay decisions is frequently negative (i.e., contractors are underpaid in the long run), especially in situations where the agency has no minimum acceptable estimated quality level provision (or it has a provision, but with a low minimum).

For acceptance plan systems related to other than pavements (e.g., bridge decks), it should be noted that optimum *n* may also be influenced considerably by the cost associated with erroneous accept/reject decisions. If the consequences of erroneous accept/reject decisions are catastrophic and could result in loss of lives, the optimum *n* could be much higher than 3. Both previous research and this study reported here considered only pavement acceptance plan systems.

Optimum *n* is of course also a function of the AQCs being measured—what are they? how many are there? are they correlated? and what is the cost to sample and test them? The number of AQCs is important as they work as a unit to estimate lot quality which then determines the composite pay factor. Because the expected cost of erroneous pay decisions is spread out among the AQCs, each AQC's contribution to the expected cost decreases as the number of AQCs increases, resulting in a smaller optimum *n* for each AQC. This study investigated systems with only two AQCs, and already optimum *n* was below 3. Correlated AQCs were not found to change the optimum $n = 3$, conclusion for PWL, provided the agency needed the correlated AQCs within the acceptance system in order to control different key distresses. The unit costs of sampling and testing derived by previous research (Gharaibeh, 2010) were deemed to be conservative and were used in this study as well.

This study concluded statewide lot quality (and therefore lot performance) is not likely to suffer if agencies that switch to smaller acceptance sample sizes take proper precautions. Some recommendations are provided below in the recommendations section. There is also reason to believe quality might actually increase for some one-sided AQCs, as statistical-risk-aware contractors tend to raise target quality to account for the increased variability of estimates from small sample sizes. In such cases, to keep from having a corresponding increase in the cost of lots, agencies that expect contractors to raise their quality levels might consider simply lowering the specified quality level. However, it is doubtful that any increase in costs due to such increases in quality would change the optimum *n*. For agencies that believe quality levels will decrease, the simple solution would be to raise the specified quality level.

7.2 Recommendations

It is strongly recommended agencies do their own optimum *n* determinations. In doing so, they will gain a better understanding of their acceptance plan systems and associated costs, and just as important, of the various underlying assumptions and their effect on optimum *n*. Having this understanding, they will be in a better position to draw their own conclusions from the performed economic decision analysis, which identifies the best decision in the long run and not necessarily the best decision with respect to a specific project or contractor or submitted quality level. The understanding will also provide the agencies greater confidence in applying economic decision analysis principles to minimize expected costs and optimize statistical risks.

Once an agency has followed the optimization procedure and determined optimum *n* for its AQCs, the agency will have simultaneously identified the optimum buyer's and seller's risks (as these statistical risks are a function of *n*). It is also possible for the agency to determine the theoretical optimum lot size since lot size affects the expected cost of erroneous acceptance decisions (an element of the optimization model).

Assuming the agency is considering switching to a lower *n* based on its optimization, the following recommendations are offered:

- In going to less acceptance testing, the agency should consider (a) placing more emphasis on the contractors' quality control programs, (b) placing more emphasis on inspection to identify isolated instances of poor quality, and/or (c) replacing programs that use contractor test results for acceptance purposes with programs that use only the agency's test results.

- The agency should include a strong retest provision in each acceptance plan to further test lots that yield borderline test results.
- If the agency can identify specific contractor(s) with a record of having submitted low quality levels in the past, the agency should consider taking appropriate action. The agency has many options, one of which is the use of an acceptance plan system with same low *n* but greater pay reductions for the specific contractor(s).
- The agency should monitor how the lower *n* is working statewide with respect to quality and cost. Here too, the agency has many options that allow it to control overall quality and cost; simply increasing/decreasing specified quality is one such option.

APPENDIX A
A PWL QUALITY MEASURE

If the quality characteristic is to be used for payment determination, the quality measure to be related to the payment must be decided upon. There are several quality measures that can be used. In past acceptance plans, the average, or the average deviation from a target value, was often used as the quality measure. However, the use of the average alone provides no measure of variability, and it is now recognized that variability is often an important predictor of performance.

Several quality measures, including percent defective (PD) and percent within limits (PWL), have been preferred in recent years because they simultaneously measure both the average level and the variability in a statistically efficient way. In this appendix, only the PWL quality measure was described for the purpose of this study.

The Transportation Research Board (TRB) glossary (TRC-E-C074, 2005) includes the following definition (where LSL and USL represent lower and upper specification limits, respectively):

- PWL-also called percent conforming.

  The percentage of the lot falling above the LSL, beneath the USL, or between the USL and LSL (PWL may refer to either the population value or the sample estimate of the population value. PWL = 100 - PD.)

This quality measure uses the sample mean and the sample standard deviation to estimate the percentage of the population (lot) that is within the specification limits. This is called the PWL method, and is similar in concept to determining the area under the normal curve.

In theory, the use of the PWL (or PD) method assumes that the population being sampled is normally distributed. In practice, it has been found that statistical estimates of quality are reasonably accurate provided the sampled population is at least approximately normal, i.e., reasonably bell shaped and not bimodal or highly skewed.

A.1 Estimating PWL

Conceptually, the PWL procedure is based on the normal distribution. The area under the normal curve can be calculated to determine the percentage of the population that is within certain limits. Similarly, the percentage of the lot that is within the specification limits can be estimated. Instead of using the Z-value and the standard normal curve, a similar statistic, the quality index, Q, is used to estimate PWL. The Q-value is used with a PWL table to determine the estimated PWL for the lot.

A sample PWL table is shown in Table A-1. A different format for a table relating Q values with the appropriate PWL estimate is shown for a sample size of n = 5 in Table A-2. A more complete set of PWL tables in this format, for sample sizes from n = 3 to n = 30, is available. Another way of relating Q and PWL values is presented in Table A-3. In this table a range of Q values is associated with each PWL value. This table was developed by an agency such that any estimated PWL is rounded up to the next integer PWL value. Other possible rounding rules could be used to develop similar tables. The rounding rule in Table A-3 is the one that is most favorable to the contractor since it rounds any PWL number up to the next whole number. For example, 89.01 is rounded up to 90.00 in Table A-3.

A.2 Calculation and Rounding Procedures

As the previous paragraph illustrates, the calculation procedures and rounding rules can influence the estimated PWL value that is obtained. This can become a point of contention, particularly if the payment determination is based on the estimated PWL value. It is therefore important that the agency stipulate the specific calculation process, including number of decimal places to be carried in the calculations, as well as the exact manner in which the PWL table is to be used.

For example, in Table A-1, is the PWL value to be selected by rounding up, rounding down, or by linear interpolation. Each of these will result in a different estimated PWL value. For instance, if the sample size is n = 5, and the calculated Q value is 1.18, the estimated PWL values for rounding up, rounding down, and interpolating would be 89, 88, and 88.5, respectively.

A.3 Quality Index and PWL

The Z-statistic that is used with the standard normal table, an example of which is shown in Table A-4, uses the population mean as the point of reference from which the area under the curve is measured:

$$Z = \frac{X - \mu}{\sigma}$$

Where:

Z = the Z-statistic to be used with a standard normal table (such as Table A-4).

X = the point within which the area under the curve is desired.

µ = the population mean.

s = the population standard deviation.

The statistic Z, therefore, measures distance above or below the mean, µ, using the number of standard deviation units, s, as the measurement scale. This is illustrated in Figure A-1.

Table A-1 Quality Index Values for Estimating PWL I

PWL	*n* = 3	*n* = 4	*n* = 5	*n* = 6	*n* = 7	*n* = 8	*n* = 9	*n* = 10 to 11
100	1.16	1.5	1.79	2.03	2.23	2.39	2.53	2.65
99	-	1.47	1.67	1.8	1.89	1.95	2	2.04
98	1.15	1.44	1.6	1.7	1.76	1.81	1.84	1.86
97	-	1.41	1.54	1.62	1.67	1.7	1.72	1.74
96	1.14	1.38	1.49	1.55	1.59	1.61	1.63	1.65
95	-	1.35	1.44	1.49	1.52	1.54	1.55	1.56
94	1.13	1.32	1.39	1.43	1.46	1.47	1.48	1.49
93	-	1.29	1.35	1.38	1.4	1.41	1.42	1.43
92	1.12	1.26	1.31	1.33	1.35	1.36	1.36	1.37
91	1.11	1.23	1.27	1.29	1.3	1.3	1.31	1.31
90	1.1	1.2	1.23	1.24	1.25	1.25	1.26	1.26
89	1.09	1.17	1.19	1.2	1.2	1.21	1.21	1.21
88	1.07	1.14	1.15	1.16	1.16	1.16	1.16	1.17
87	1.06	1.11	1.12	1.12	1.12	1.12	1.12	1.12
86	1.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08
85	1.03	1.05	1.05	1.04	1.04	1.04	1.04	1.04
84	1.01	1.02	1.01	1.01	1	1	1	1
83	1	0.99	0.98	0.97	0.97	0.96	0.96	0.96
82	0.97	0.96	0.95	0.94	0.93	0.93	0.93	0.92
81	0.96	0.93	0.91	0.9	0.9	0.89	0.89	0.89
80	0.93	0.9	0.88	0.87	0.86	0.86	0.86	0.85
79	0.91	0.87	0.85	0.84	0.83	0.82	0.82	0.82
78	0.89	0.84	0.82	0.8	0.8	0.79	0.79	0.79
77	0.87	0.81	0.78	0.77	0.76	0.76	0.76	0.75
76	0.84	0.78	0.75	0.74	0.73	0.73	0.72	0.72
75	0.82	0.75	0.72	0.71	0.7	0.7	0.69	0.69
74	0.79	0.72	0.69	0.68	0.67	0.66	0.66	0.66
73	0.76	0.69	0.66	0.65	0.64	0.63	0.63	0.63
72	0.74	0.66	0.63	0.62	0.61	0.6	0.6	0.6
71	0.71	0.63	0.6	0.59	0.58	0.57	0.57	0.57
70	0.68	0.6	0.57	0.56	0.55	0.55	0.54	0.54
69	0.65	0.57	0.54	0.53	0.52	0.52	0.51	0.51
68	0.62	0.54	0.51	0.5	0.49	0.49	0.48	0.48
67	0.59	0.51	0.47	0.47	0.46	0.46	0.46	0.45

PWL	*n* = 3	*n* = 4	*n* = 5	*n* = 6	*n* = 7	*n* = 8	*n* = 9	*n* = 10 to 11
65	0.52	0.45	0.43	0.41	0.41	0.4	0.4	0.4
64	0.49	0.42	0.4	0.39	0.38	0.38	0.37	0.37
63	0.46	0.39	0.37	0.36	0.35	0.35	0.35	0.34
62	0.43	0.36	0.34	0.33	0.32	0.32	0.32	0.32
61	0.39	0.33	0.31	0.3	0.3	0.29	0.29	0.29
60	0.36	0.3	0.28	0.27	0.27	0.27	0.26	0.26
59	0.32	0.27	0.25	0.25	0.24	0.24	0.24	0.24
58	0.29	0.24	0.23	0.22	0.21	0.21	0.21	0.21
56	0.22	0.18	0.17	0.16	0.16	0.16	0.16	0.16
55	0.18	0.15	0.14	0.14	0.13	0.13	0.13	0.13
54	0.14	0.12	0.11	0.11	0.11	0.11	0.1	0.1
53	0.11	0.09	0.08	0.08	0.08	0.08	0.08	0.08
52	0.07	0.06	0.06	0.05	0.05	0.05	0.05	0.05
51	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03
50	0	0	0	0	0	0	0	0

Table A-1 Quality Index Values for Estimating PWL I (continued)

Table A-1 Quality Index Values for Estimating PWL II

PWL	*n* = 12 to 14	*n* = 15 to 18	*n* = 19 to 25	*n* = 26 to 37	*n* = 38 to 69	*n* = 70 to 200	*n* = 201 to ∞
72	0.59	0.59	0.59	0.59	0.59	0.58	0.58
71	0.57	0.56	0.56	0.56	0.56	0.55	0.55
70	0.54	0.53	0.53	0.53	0.53	0.53	0.52
69	0.51	0.5	0.5	0.5	0.5	0.5	0.5
68	0.48	0.48	0.47	0.47	0.47	0.47	0.47
67	0.45	0.45	0.45	0.44	0.44	0.44	0.44
66	0.42	0.42	0.42	0.42	0.41	0.41	0.41
65	0.4	0.39	0.39	0.39	0.39	0.39	0.39
64	0.37	0.36	0.36	0.36	0.36	0.36	0.36
63	0.34	0.34	0.34	0.34	0.33	0.33	0.33
62	0.31	0.31	0.31	0.31	0.31	0.31	0.31
61	0.29	0.29	0.28	0.28	0.28	0.28	0.28
60	0.26	0.26	0.26	0.26	0.26	0.25	0.25
59	0.23	0.23	0.23	0.23	0.23	0.23	0.23
58	0.21	0.21	0.2	0.2	0.2	0.2	0.2
57	0.18	0.18	0.18	0.18	0.18	0.18	0.18

PWL	*n* = 12 to 14	*n* = 15 to 18	*n* = 19 to 25	*n* = 26 to 37	*n* = 38 to 69	*n* = 70 to 200	*n* = 201 to ∞
56	0.16	0.15	0.15	0.15	0.15	0.15	0.15
55	0.13	0.13	0.13	0.13	0.13	0.13	0.13
54	0.1	0.1	0.1	0.1	0.1	0.1	0.1
53	0.08	0.08	0.08	0.08	0.08	0.08	0.08
52	0.05	0.05	0.05	0.05	0.05	0.05	0.05
51	0.03	0.03	0.03	0.03	0.03	0.03	0.02
50	0	0	0	0	0	0	0

Table A-1 Quality Index Values for Estimating PWL II (continued)

Table A-2 PWL Estimation Table for Sample Size n = 5

Q	0	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0	50	50.36	50.71	51.07	51.42	51.78	52.13	52.49	52.85	53.2
0.1	53.56	53.91	54.27	54.62	54.98	55.33	55.69	56.04	56.39	56.75
0.2	57.1	57.46	57.81	58.16	58.52	58.87	59.22	59.57	59.92	60.28
0.3	60.63	60.98	61.33	61.68	62.03	62.38	62.72	63.07	63.42	63.77
0.4	64.12	64.46	64.81	65.15	65.5	65.84	66.19	66.53	66.87	67.22
0.5	67.56	67.9	68.24	68.58	68.92	69.26	69.6	69.94	70.27	70.61
0.6	70.95	71.28	71.61	71.95	72.28	72.61	72.94	73.27	73.6	73.93
0.7	74.26	74.59	74.91	75.24	75.56	75.89	76.21	76.53	76.85	77.17
0.8	77.49	77.81	78.13	78.44	78.76	79.07	79.38	79.69	80	80.31
0.9	80.62	80.93	81.23	81.54	81.84	82.14	82.45	82.74	83.04	83.34
1	83.64	83.93	84.22	84.52	84.81	85.09	85.38	85.67	85.95	86.24
1.1	86.52	86.8	87.07	87.35	87.63	87.9	88.17	88.44	88.71	88.98
1.2	89.24	89.5	89.77	90.03	90.28	90.54	90.79	91.04	91.29	91.54
1.3	91.79	92.03	92.27	92.51	92.75	92.98	93.21	93.44	93.67	93.9
1.4	94.12	94.34	94.56	94.77	94.98	95.19	95.4	95.61	95.81	96.01
1.5	96.2	96.39	96.58	96.77	96.95	97.13	97.31	97.48	97.65	97.81
1.6	97.97	98.13	98.28	98.43	98.58	98.72	98.85	98.98	99.11	99.23
1.7	99.34	99.45	99.55	99.64	99.73	99.81	99.88	99.94	99.98	100

Table A-3 Another PWL Estimation Table for Sample Size n = 5

Q_L or Q_U	PWL_L or PWL_U
1.671 or More	100
1.601 to 1.670	99
1.541 to 1.600	98
1.491 to 1.540	97
1.441 to 1.490	96
1.391 to 1.440	95
1.351 to 1.390	94
1.311 to 1.350	93
1.271 to 1.310	92
1.231 to 1.270	91
1.191 to 1.230	90
1.151 to 1.190	89
1.121 to 1.150	88
1.081 to 1.120	87
1.051 to 1.080	86
1.011 to 1.050	85
0.981 to 1.010	84
0.951 to 0.980	83
0.911 to 0.950	82
0.881 to 0.910	81
0.851 to 0.880	80
0.821 to 0.850	79
0.781 to 0.820	78

Q_L or Q_U	PWL_L or PWL_U
-0.029 to 0.000	50
-0.059 to -0.030	49
-0.079 to -0.060	48
-0.109 to -0.080	47
-0.139 to -0.110	46
-0.169 to -0.140	45
-0.199 to -0.170	44
-0.229 to -0.200	43
-0.249 to -0.230	42
-0.279 to -0.250	41
-0.309 to -0.280	40
-0.339 to -0.310	39
-0.369 to -0.340	38
-0.399 to -0.370	37
-0.429 to -0.400	36
-0.449 to -0.430	35
-0.469 to -0.450	34
-0.509 to -0.470	33
-0.539 to -0.510	32
-0.569 to -0.540	31
-0.599 to -0.570	30
-0.629 to -0.600	29
-0.659 to -0.630	28

Q_L or Q_U	PWL_L or PWL_U
0.751 to 0.780	77
0.721 to 0.750	76
0.691 to 0.720	75
0.661 to 0.690	74
0.631 to 0.660	73
0.601 to 0.630	72
0.571 to 0.600	71
0.541 to 0.570	70
0.511 to 0.540	69
0.471 to 0.510	68
0.451 to 0.470	67
0.431 to 0.450	66
0.401 to 0.430	65
0.371 to 0.400	64
0.341 to 0.370	63
0.311 to 0.340	62
0.281 to 0.310	61
0.251 to 0.280	60
0.231 to 0.250	59
0.201 to 0.230	58
0.171 to 0.200	57
0.141 to 0.170	56
0.111 to 0.140	55

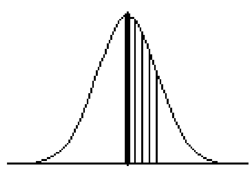
Q_L or Q_U	PWL_L or PWL_U
-0.689 to -0.660	27
-0.719 to -0.690	26
-0.749 to -0.720	25
-0.779 to -0.750	24
-0.819 to -0.780	23
-0.849 to -0.820	22
-0.879 to -0.850	21
-0.909 to -0.880	20
-0.949 to -0.910	19
-0.979 to -0.950	18
-1.009 to -0.980	17
-1.049 to -1.010	16
-1.079 to -1.050	15
-1.119 to -1.080	14
-1.149 to -1.120	13
-1.189 to -1.150	12
-1.229 to -1.190	11
-1.269 to -1.230	10
-1.309 to -1.270	9
-1.349 to -1.310	8
-1.389 to -1.350	7
-1.439 to -1.390	6
-1.489 to -1.440	5

Q_L or Q_U	PWL_L or PWL_U
0.081 to 0.110	54
0.061 to 0.080	53
0.031 to 0.060	52
0.001 to 0.030	51
-0.029 to 0.000	50

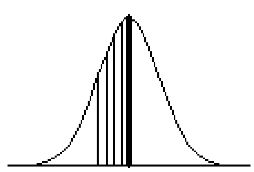
Q_L or Q_U	PWL_L or PWL_U
-1.539 to -1.490	4
-1.599 to -1.540	3
-1.669 to -1.600	2
-1.789 to -1.670	1
-1.790 or Less	0

Table A-3 Another PWL Estimation Table for Sample Size n = 5

Table A-4 Areas Under the Standard Normal Distribution



or



Z	**.00**	**.01**	**.02**	**.03**	**.04**	**.05**	**.06**	**.07**	**.08**	**.09**
.0	.0000	.0040	.0080	.0120	.0160	.0199	.0239	.0279	.0319	.0359
.1	.0398	.0438	.0478	.0517	.0557	.0596	.0636	.0675	.0714	.0753
.2	.0793	.0832	.0871	.0910	.0948	.0987	.1026	.1064	.1103	.1141
.3	.1179	.1217	.1255	.1293	.1331	.1368	.1406	.1443	.1480	.1517
.4	.1554	.1591	.1628	.1664	.1700	.1736	.1772	.1808	.1844	.1879
.5	.1915	.1950	.1985	.2019	.2054	.2088	.2123	.2157	.2190	.2224
.6	.2257	.2291	.2324	.2357	.2389	.2422	.2454	.2486	.2517	.2549
.7	.2580	.2611	.2642	.2673	.2704	.2734	.2764	.2794	.2823	.2852

Z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
.8	.2881	.2910	.2939	.2967	.2995	.3023	.3051	.3078	.3106	.3183
.9	.3159	.3186	.3212	.3238	.3264	.3289	.3315	.3340	.3365	.3389
1.0	.3413	.3438	.3461	.3485	.3508	.3531	.3554	.3577	.3599	.3621
1.1	.3643	.3665	.3686	.3708	.3729	.3749	.3770	.3790	.3810	.3830
1.2	.3849	.3869	.3888	.3907	.3925	.3944	.3962	.3980	.3997	.4015
1.3	.4032	.4049	.4066	.4082	.4099	.4115	.4131	.4147	.4162	.4177
1.4	.4192	.4207	.4222	.4236	.4251	.4265	.4279	.4292	.4306	.4319
1.5	.4332	.4345	.4357	.4370	.4382	.4394	.4406	.4418	.4429	.4441
1.6	.4452	.4463	.4474	.4484	.4495	.4505	.4515	.4525	.4535	.4545
1.7	.4554	.4564	.4573	.4582	.4591	.4599	.4608	.4616	.4625	.4633
1.8	.4641	.4649	.4656	.4664	.4671	.4678	.4686	.4693	.4699	.4706
1.9	.4713	.4719	.4726	.4732	.4738	.4744	.4750	.4756	.4761	.4767
2.0	.4772	.4778	.4783	.4788	.4793	.4798	.4803	.4808	.4812	.4817
2.1	.4821	.4826	.4830	.4834	.4838	.4842	.4846	.4850	.4854	.4857
2.2	.4861	.4864	.4868	.4871	.4875	.4878	.4881	.4884	.4887	.4890
2.3	.4893	.4896	.4898	.4901	.4904	.4906	.4909	.4911	.4913	.4916
2.4	.4918	.4920	.4922	.4925	.4927	.4929	.4931	.4932	.4934	.4936
2.5	.4938	.4940	.4941	.4943	.4945	.4946	.4948	.4949	.4951	.4952
2.6	.4953	.4955	.4956	.4957	.4959	.4960	.4961	.4962	.4963	.4964
2.7	.4965	.4966	.4967	.4968	.4969	.4970	.4971	.4972	.4973	.4974
2.8	.4974	.4975	.4976	.4977	.4977	.4978	.4979	.4979	.4980	.4981
2.9	.4981	.4982	.4982	.4983	.4984	.4984	.4985	.4985	.4986	.4986
3.0	.4987	.4987	.4987	.4988	.4988	.4989	.4989	.4989	.4990	.4990
3.1	.4990	.4991	.4991	.4991	.4992	.4992	.4992	.4992	.4993	.4993
3.2	.4993	.4993	.4994	.4994	.4994	.4994	.4994	.4995	.4995	.4995
3.3	.4995	.4995	.4995	.4996	.4996	.4996	.4996	.4996	.4996	.4997
3.4	.4997	.4997	.4997	.4997	.4997	.4997	.4997	.4997	.4997	.4998

Table A-4 Areas Under the Standard Normal Distribution (continued)

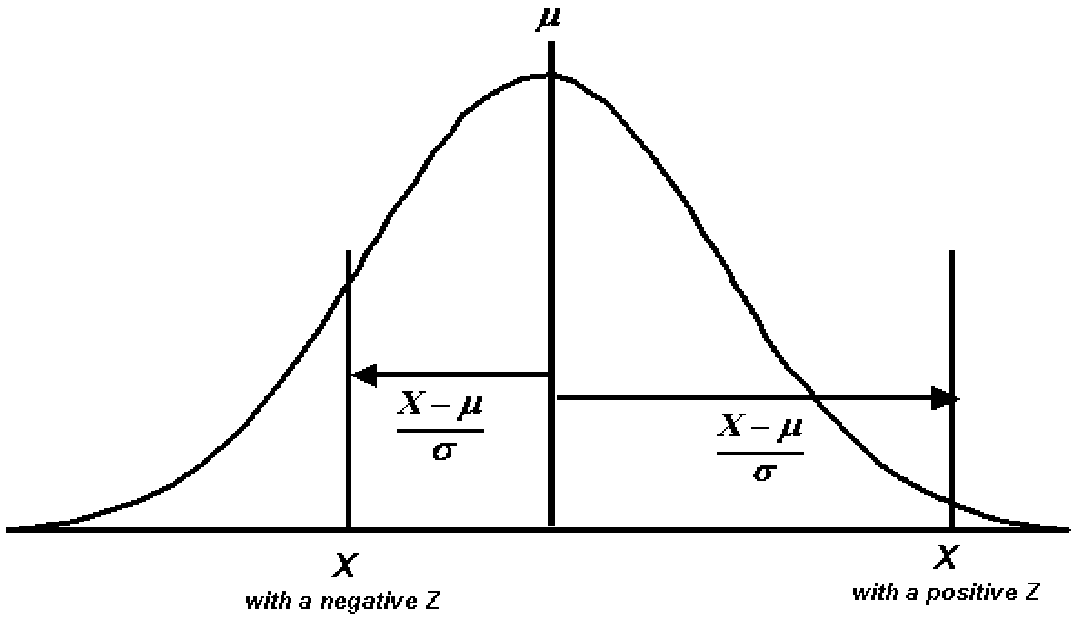


Figure A-1. Illustration of the Calculation of the Z -statistic

Conceptually, the *Q*-statistic, or *quality index*, performs identically the same function as the *Z*-statistic except that now the reference point is the mean of an individual sample, $\overline{X}$, instead of the population mean, *μ*, and the points of interest with regard to areas under the curve are the specification limits.

$$Q_L = \frac{\overline{X} - LSL}{s}$$

and

$$Q_U = \frac{USL - \overline{X}}{s}$$

Where:

Q_L = quality index for the lower specification limit.

Q_U = quality index for the upper specification limit.

LSL = lower specification limit.

USL = upper specification limit.

$\overline{X}$ = the sample mean for the lot.

s = the sample standard deviation for the lot.

The Q-statistic, therefore, represents the distance in sample standard deviation units that the sample mean is offset from the specification limit. A positive Q-statistic represents the number of sample standard deviation units that the sample mean falls inside the specification limit. Conversely, a negative Q-statistic represents the number of sample standard deviation units that the sample mean falls outside the specification limit. These cases are illustrated in Figures A-2 and A-3.

Q_L is used when there is a one-sided lower specification limit, while Q_U is used when there is a one-sided upper specification limit. For two-sided specification limits, the PWL value is estimated as:

$PWL_T = PWL_U + PWL_L - 100$

Where:

PWL_U = percent below the upper specification limit (based on QU).

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

PWL_T = percent within the upper and lower specification limits.

A.4 Example

An example using a simplified Portland cement concrete specification can be used to explain the PWL concept. In this example, the minimum specification limit for strength is 21,000 kPa. One requirement of the PWL procedure is that the sample size must be greater than n = 2 since both the sample mean and sample standard deviation are necessary to estimate PWL. For this specification, the sample size has been chosen as n = 4. Furthermore, the specification requires that at least 95 percent of the lot exceed the minimum strength (i.e., PWL > 95). Table A-1 shows that the minimum Q value is 1.35 for 95 PWL and a sample size of n = 4. Whenever the mean is 1.35s above the specification limit, the lot is accepted. However, as used most frequently, the Q value will be used to compute the PWL and that will, in turn, be used to determine a payment factor.

For example, suppose that the acceptance tests for a lot have a sample mean of 25,000 kPa and a sample standard deviation of 3,400 kPa. Does this lot meet the specification requirement? The quality index value is calculated as:

$$Q_L = \frac{25000 - 21000}{3400} = 1.18$$

Using this Q-value, n = 4, and Table A-1, the estimated PWL for the lot is between 89 and 90. This is less than the required 95, so the lot does not meet the specified strength requirement.

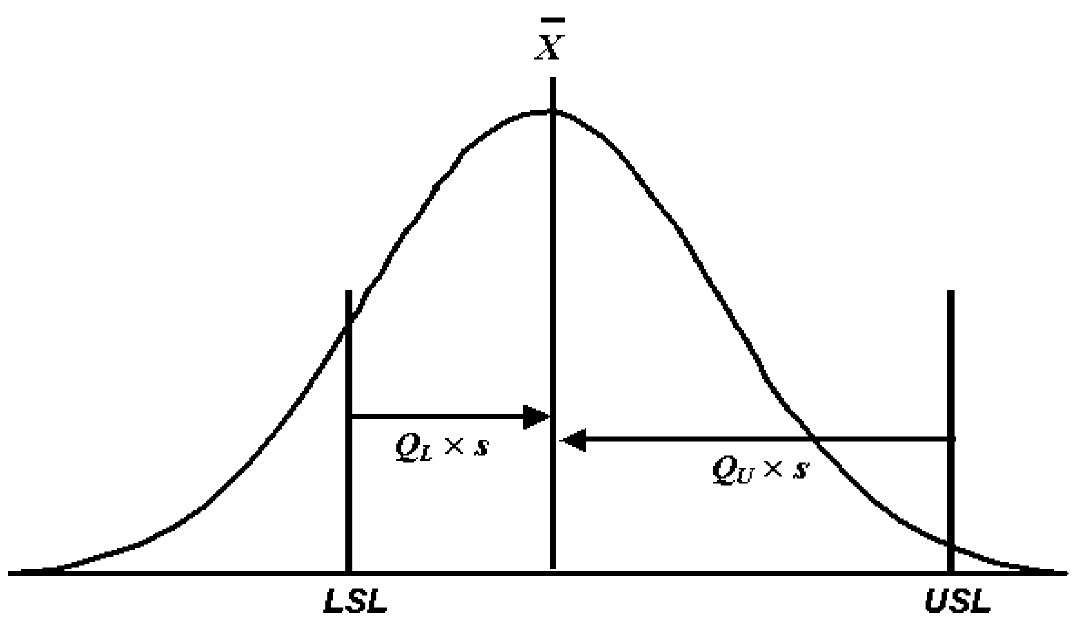


Figure A-2. Illustration of Positive Quality Index Values

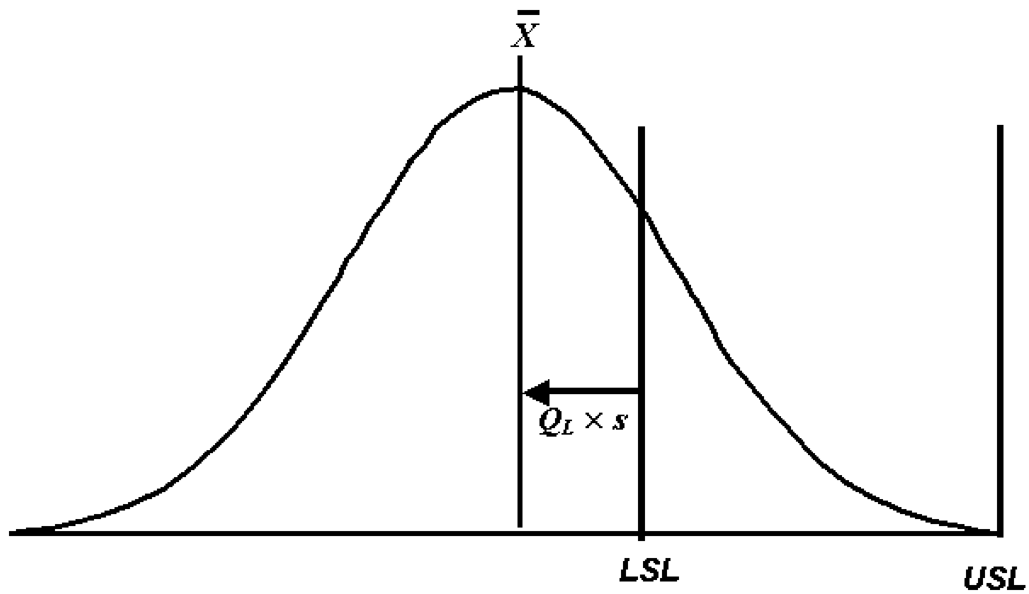


Figure A-3. Illustration of a Negative Quality Index Value

Intuitively, PWL is a good measure of quality since it is reasonable to assume that the more of the material that is within the specification limits, the better the quality of the product should be. A detailed discussion and analysis of the PWL measure of quality is presented in the technical report for the project.

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BIOGRAPHICAL SKETCH

Dooyong Cho was born in Seoul, Republic of Korea. He started his college career at SungKyunKwan University in Seoul. He earned Bachelor of Science and Master of Science degrees, majoring in civil engineering in 2002. He came over United States of America to study abroad in 2002. At Pennsylvania State University, he earned Master of Engineering degree in the Department of Civil and Environmental engineering. He transferred to and entered in a Ph.D program in the Civil and Coastal Engineering Department at the University of Florida in 2005 in Ph.D program specializing in infrastructural engineering and public works.