A new method of determining payment for in-place concrete with double-bounded compressive strength pay factors

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The Transportation Infrastructure Durability Center (TIDC) is the 2018 US DOT Region 1 (New England) University Transportation Center (UTC) located at the University of Maine Advanced Structures and Composites Center. TIDC's research focuses on efforts to improve the durability and extend the life of transportation infrastructure in New England and beyond through an integrated collaboration of universities, state DOTs, and industry. The TIDC is comprised of six New England universities, the University of Maine (lead), the University of Connecticut, the University of Massachusetts Lowell, the University of Rhode Island, the University of Vermont, and Western New England University.

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List of Key Terms

concrete compressive strength (CCS)
percent-within-limits (PWL)
random variables (RVs)
probability distribution function (PDF)
quality assurance (QA) / quality control (QC) performance specification
percent-within-distribution (PWD)

Bayes process: a method of statistical inference that allows one to combine prior information about a population with evidence from a sample to guide the statistical inference process
acceptance boundary, acceptance limit, acceptance threshold, or acceptance range: the limits or boundaries (upper and lower) that determine the quality of our results; observations falling within that range are accepted and those falling outside the range are rejected
design distribution: the desired distribution of a sample; used to determine payment rewards and penalties
pay factors: the schedule of payment rewards and penalties that correspond with a variety of quality measures calculated from a sample
decision-support tool: software developed to support analysts and decision makers in making better decisions, faster

Abstract

The Vermont Agency of Transportation currently uses a lower acceptance limit on 28-day concrete compressive strength (CCS) of 4,000 psi for acceptance of in-place concrete in its construction projects, particularly for placement of bridge decks. Over time, to reduce risk, the concrete industry's response has led to increasingly higher average 28-day CCS, which is believed to be associated with increased brittleness and excessive early cracking. These findings have led to a recommendation to establish a target mean CCS of around 5,000 psi with pay factors and they support the argument for including an upper acceptance limit when CCS is used as a performance characteristic. Under this type of performance specification, pay factors are typically enforced for payment using the percent-within-limits (PWL) quality measure. A drawback of the PWL is its implicit assumption that the distribution of 28-day CCS is Gaussian so that z-scores can be used for assessment of payment. Our research team's review of the literature and historical data suggests that the distribution of resulting industry-wide CCS is not likely to be Gaussian, especially once the double-bounded acceptance range is implemented. The goal of this project was to develop a new quality measure for payment of in-place CCS that does not rely on the Gaussian distribution and allows a variety of pay factors around the target mean. A new approach was developed, called the percent-within-distribution (PWD), which calculates a quality measure from a 28-day CCS sample by comparing the sample to any type of design distribution using a Bayes process. Random variables were used to guide the new approach and the simulated responses that the industry might take. We showed how the new quality measure can be used for acceptance and payment under a double-bounded pay factor schedule, but also how it could be used to design a pay factor schedule in the absence of complete lifecycle cost data. The research team also created a decision-support tool to manage the implementation of the new approach. The tool allows the user to specify and visualize their design distribution, then calculate the PWD from a sample. The tool is based in MS Excel so that it will be useful to a variety of DOT QA/QC personnel.

Chapter 1: Introduction

1.1 Project Motivation

The Vermont Agency of Transportation (VTrans) currently uses a lower acceptance limit on 28-day concrete compressive strength (CCS) of 4,000 psi for acceptance of in-place concrete in its construction projects. VTrans' use of concrete is particularly relevant to its placement of bridge decks. Currently, VTrans does not use pay factors to penalize payment for CCS lot averages that far exceed the lower acceptance limit of 4,000 psi. Over time, to reduce risk, the concrete industry's (suppliers and contractors) response has led to increasingly higher average 28-day CCS, which is believed to be associated with increased brittleness and excessive early cracking, and they support the argument for including an upper acceptance limit when CCS is used as a performance characteristic.

Once implemented, pay factors are typically enforced for payment using the percent-within-limits (PWL) quality measure (Burati et al., 2003). A drawback of the PWL is its implicit assumption that the distribution of 28-day CCS is Gaussian, and its limitations in assessing payment when an upper acceptance limit is used. The goal of this project was to develop a new quality measure for payment of in-place CCS that does not rely on the Gaussian distribution and allows for the use of a variety of pay factor schedules.

VTrans' intent is to use new pay factors to create incentives for its contractors that will yield 28-day CCS that are within a specified strength range and focused on a target mean that is lower than what they have been receiving. UVM researchers worked with VTrans' Materials Testing & Certification Lab to develop a set of initial pay factors for payment of in-place concrete, employing a scenario-based heuristic approach that balances Agency risk with several likely scenarios for an initial industry response to pay factors with upper and lower acceptance limits on 28-day CCS. Pay factors for each scenario were derived by constraining the final payment to an average of 3% more than a comparable payment without pay factors.

The PWL quality measure outlined in Burati et. al (2003) was followed, since it contained the only known guidance for an approach to enforcing pay factors with an upper and lower boundary on acceptance. That work resulted in a publication in the International Journal of Quality & Reliability Management by PIs on this project, co-authored with three VTrans' Materials Testing & Certification Lab staff:

> *Novak, David C., James L. Sullivan, Jeremy Reed, Mladen Gagulic, and Nick Van Den Berg, 2018. Performance-related specification and payment modifiers in highway construction projects. International Journal of Quality & Reliability Management, Vol. 35 Issue: 10, pp. 2348-2372.*

The success of that research effort, and ensuing meetings with leading industry representatives, has led VTrans to decide to implement this double-bounded, pay-factor approach with a target mean. Vermont may be the first state to implement this type of QA/QC performance specification for CCS.

1.2 Research Objectives, and Tasks

The overall objectives of this research were to:

I. Develop a new quality measure for payment of in-place CCS that does not rely on the assumption of symmetry implied by the Gaussian distribution for the industry response, and allows for the use of asymmetrical set of pay factors
II. Forecast the evolution of pay factors in response to expected industry behavior in response to the new QA/QC performance specification

The following tasks were undertaken to accomplish these objectives:

- Task 1: Develop the New Approach
- Task 2: Demonstrate the Implementation of the New Approach for 3 Forecast Scenarios
- Task 3: Create a Tool to Manage the Implementation of the New Approach

1.3 Report Overview

Chapter 2 contains a description of the methodology used to develop and test the new quality measure, the way that the industry response to the double-bounded pay factor system would be simulated, and how these simulations would be used to develop pay factors. Chapter 2 also contains a brief description of the platform used to develop the decision-support tool. Chapter 3 provides a summary of the results of the testing of the new quality measure, the simulation of the industry response, and the development of pay factors. Chapter 3 also contains important discussion points that need to be considered for the use of the PWD as a quality measure. Chapter 4 contains the conclusions of the project, and recommendations for implementation of a double-bounded pay factor system with the PWD quality measure and the MS Excel tool.

Chapter 2: Methodology

2.1 Development of the New Approach

A new quality measure and accompanying algorithm for acceptance and payment with pay factors for a QA/QC performance specification addresses the shortcomings of the PWL-based method. Instead of requiring only a lower acceptance limit and relying on the assumption of a Gaussian distribution, the new approach requires a design distribution type, a design mean, a design standard deviation, and an acceptance range, determining the fit of the contractor's observed CCS data to these design parameters. From this fit, a new quality measure is calculated. In this project, the new approach was demonstrated for Gaussian, Gamma, and Weibull design distributions. The innovative quality measure is called the percent-within-distribution, or PWD. The algorithm developed re-estimates the parameters of the design distribution after considering the sample in a Bayes process, then calculates a PWD. It can be used for any size sample lot with a design distribution, design mean, design standard deviation, and acceptance range. The PWD is calculated by comparing the final distribution estimated from all of the observations with the design distribution. A Bayes process is perfectly suited to this application because we can assume that the contractor has knowledge of the design distribution through the QA/QC performance specification, so observations can be considered new realizations of the design distribution, with variations in the parameters resulting from the random error arising from the contractor's attempts.

The method algorithm was originally implemented in Matlab 2021b. Applying the algorithm to a sample yields two distributions – *the design distribution* ($f_{design}(x)$) and *the distribution suggested by the sample* ($f(x)$). The PWD, then, is calculated as the fraction of $f(x)$ that falls under $f_{design}(x)$ and within the acceptance range, divided by the fraction of $f(x)$ within the acceptance range. The PWD indicates the degree to which $f(x)$ is similar to $f_{design}(x)$. The PWL is simply the area under $f(x)$ within the acceptance range divided by the total area under $f(x)$ without regard to the acceptance range.

It is important to note that the PWD will be the same regardless of the order that the samples are fed through the algorithm. However, due to the use of a Bayes updating step in the algorithm, the PWD will tend to go down as additional samples are fed through. Therefore, it is not advisable to compare PWDs for sample lots of different sizes using the PWD.

With only the PWL as a quality measure, it would be difficult for us to discern differences in quality between sample lots when they consistently yield PWLs of 100%. Contrastingly, the PWD exhibits a higher level of sensitivity. Even a modest change in one of the samples in a lot can yield a significant difference in the resulting PWD, and the entire lot must be very close to the peak of the design distribution before values close to 100% can be achieved. Considering a design mean of 5,200 psi, a design standard deviation of 800 psi, a Weibull design distribution, and an acceptance range from 4,000 to 8,500 psi, a sample of size 7 that is very close to the design distribution [5970 5215 5871 4713 4738 4439 6057] yields a PWD of 96%, indicating that it will be very difficult for a contractor to get a PWD above 99% in this scenario. However, the PWL for this example is 100%.

Therefore, it is important to examine the sensitivity of the PWD to a variety of samples from a specific design distribution before determining a pay factor schedule. If a maximum realistic value of the PWD exists for an ideal sample from a certain design distribution, we would want that quality measure to yield the highest rewarding pay factor. In other words, we would never want to penalize the contractor incorrectly due to random error when they may have achieved an ideal sample.

Setting pay factors without comprehensive data regarding the life cycle cost of the material that is being subjected to a performance specification requires the use of a simulated industry response and a targeted industry-wide payment reward. With a targeted reward, the PWD can be used to establish an initial set of pay factors that correspond to the new quality measure. An initial pay factor schedule is first created by choosing an overpayment amount, a peak pay-factor reward, and a step size to decrease the pay factor for every % point of PWD lost. Then, samples are simulated from the design distribution. Since these simulations are based on the design distribution, they are initially designed to be rewarded at the peak pay factor. In fact, PWDs that are at a lower percentile of the simulation samples should still be reasonably expected to yield a full reward. Therefore, the first step in the setting of initial pay factors is to establish the lowest possible PWD that will still yield a full reward. From this point, a decreasing set of pay factors according to the step size are set to assess payment for a full schedule of PWDs. From that point, a realistic set of samples are simulated to represent the expected industry response, PWDs are calculated, and pay factors are applied. This process is repeated to simulate a full construction season of samples. Then the peak pay factor reward and the step size for the pay factor schedule are adjusted until the simulated payments meet the targeted overpayment amount. An example is provided in Chapter 3.

2.2 Modeling of Industry Response

The implementation of a double-bounded pay factor system requires an iterative, progressive approach that includes an expectation for how the industry will respond over a given time period. Typically, a new QA/QC performance specification like this is implemented with low rewards and low penalties in the early years, then evolves with higher rewards and penalties as the industry evolves to produce material that is closer to the design distribution. In this project, the industry response was assumed to occur gradually, with little or no response in the first construction season, followed by a muted response, and concluding with a more dramatic shift toward the design distribution.

To model the immediate (0-2 years) industry response, we assumed that the industry simply incorporates the risks and penalties of the pay factor system into its unit rates, but does not change its production processes, except to avoid overly strong material that would be rejected. Therefore, the simulation of the first few construction seasons included sample lots generated through a random selection of values between the lower and upper acceptance range.

To model the transitionary (2-4 years) industry response, we assumed that the industry has evolved to make a partial shift in the peak and/or the variance of the distribution of CCS toward the design distribution, continuing to avoid overly strong material that might be rejected. Therefore, the simulation of the 2^{nd} through the 4^{th} construction seasons included sample lots generated through a randomized selection of values from the design distribution with the mean or the variance shifted down.

Finally, to model the long-term (4+ years) industry response, we assumed that the industry has evolved to make a larger shift in the peak of the distribution, while holding the variance tight enough to avoid samples below the lower acceptance limit of 4,000 psi. Therefore, the simulation of construction seasons 4 or more years after the introduction of the double-bounded pay factor system included sample lots generated through a randomized selection of values from the design distribution with the mean or the variance shifted down close to the design distribution.

2.3 Development of the Decision-Support Tool

MS Excel offers a powerful yet user-friendly computational platform for automating calculations as relevant inputs change. The team developed an Excel-based decision-support tool to run the algorithm for calculating the PWD from a sample lot. The tool will allow other users who implement a double-bounded pay factor system to calculate the PWD quality measure and determine payment of in-place concrete. Spreadsheet-based decision-support tools built in Excel allow users to change inputs, and view results in real-time. The tool was created as an extension of Excel using Visual Basic for Applications (VBA), the programming language for Excel. With VBA, a user-friendly interface can be built in the familiar spreadsheet environment when the file is saved as a macro-enabled spreadsheet (.xlsm). When the user is not likely to be interested in the underlying algorithm, this type of extension is perfectly suited. The familiar spreadsheet interface gives users total access to the algorithm's functionality via simple inputs and provides results immediately.

Chapter 3: Results and Discussion

The use of the decision-support tool is explained and demonstrated in this chapter, through its use in running the algorithm for the results presented herein. All of the results, figures, and charts presented in this chapter come from the MS Excel VBA tool.

3.1 Development and Testing Results

In the first of three worksheets that comprise the decision-support tool, the user can input the parameters of the design distribution. Since some users will not be familiar with the shape of all 3 distribution types (Gaussian, Weibull, and Gamma), a chart is also provided which illustrates the shape of the design distribution as the user makes selections. The layout of the first worksheet is shown in Figure 1.

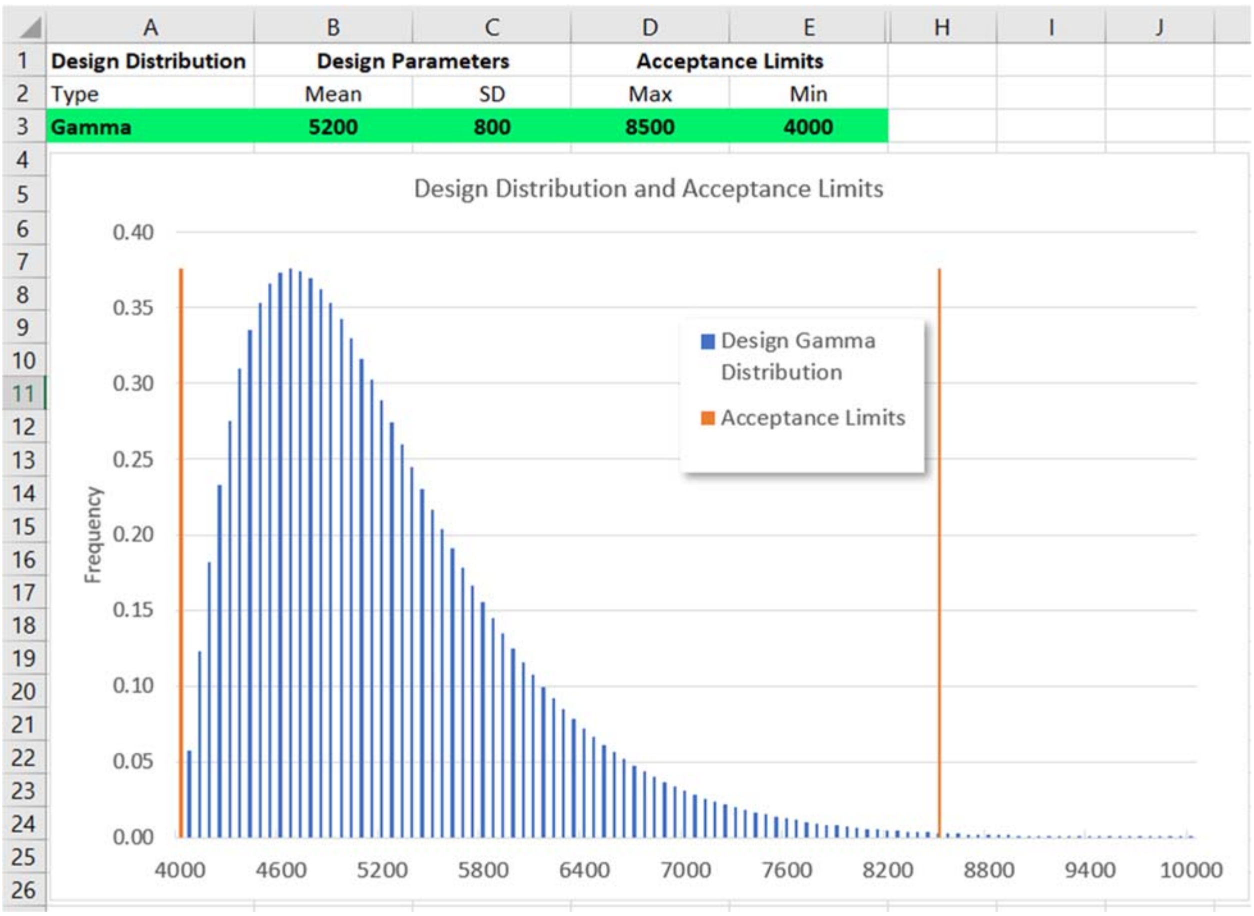

Figure 1 Initial worksheet in the decision-support tool

The chart illustrating the PDF of the selected design distribution is shown as a bar chart to remind the user that it represents a histogram of 28-day CCS values, as shown along the x-axis. Note that changing the distribution type in the dropdown box in cell A3 immediately changes the shape of the PDF, as shown in Figure 2.

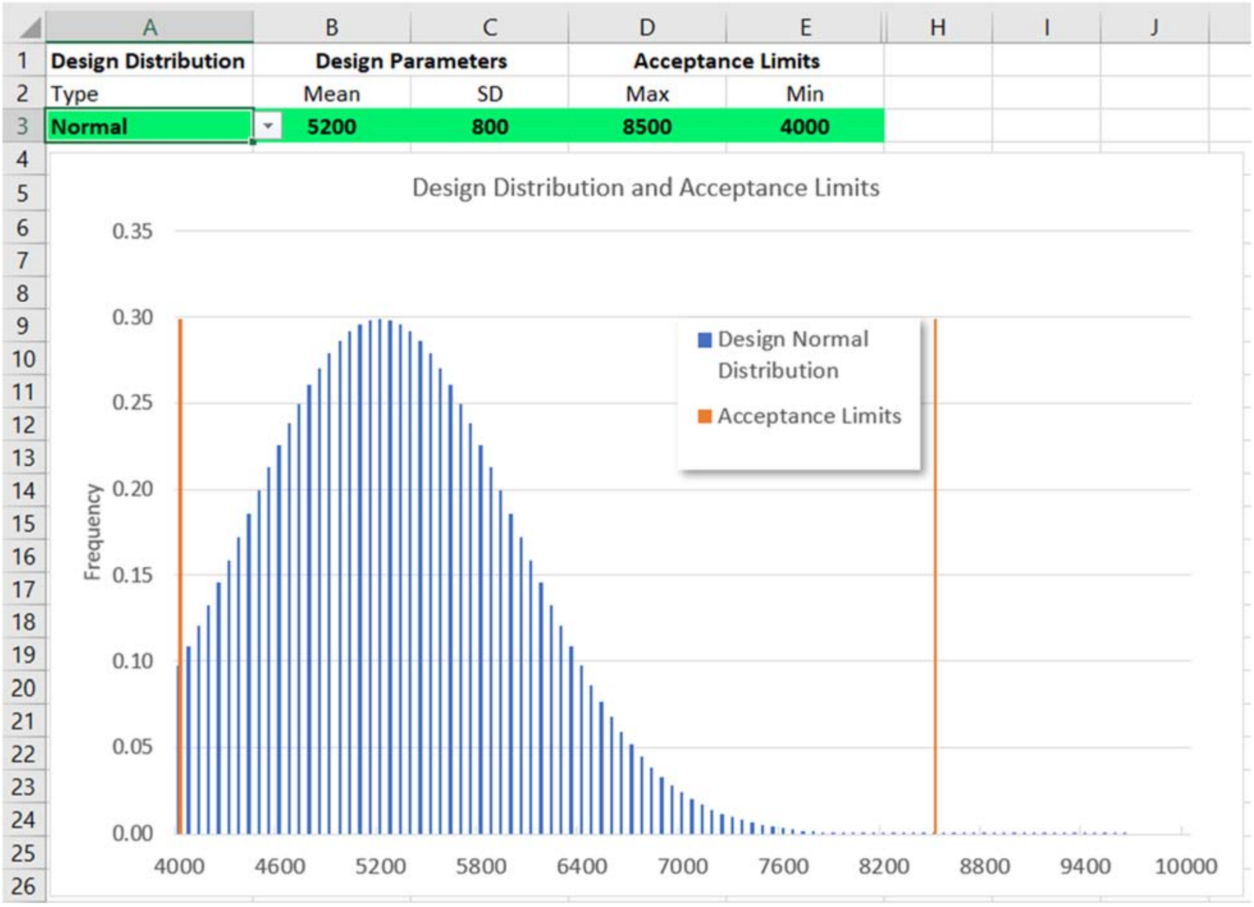

Figure 2 Initial worksheet in the Decision-Support Tool with changed the distribution type

Note in Figure 2 also how ill-suited a design Gaussian distribution is to a double-bounded acceptance range with an off-center mean. A sizeable portion of the PDF represents samples below 4,000 psi, which would be rejected under the QA/QC performance specification. The nature of the Gamma and Weibull distributions would prevent this inconsistency from occurring, since their PDFs are only defined for x values greater than 0, which are benchmarked at the lower acceptance limit in this algorithm.

The second worksheet of the decision-support tool provides a table where the new sample lot is entered, and the algorithm is initiated by clicking the button labeled "Find the PWD", as shown in Figure 3.

	A	B	C	D	E	F	G	H	I
1						m.a.p. estimate of			
2	New Lot Sample	Downscaled Sample	Bayes Evidence	Normal μ (Mean)	Normal σ (Std Dev)	Gamma α	Gamma β	Weibull k	Weibull λ
3				2.00	1.33	2.25	0.89	1.53	2.22
4	4987	1.65	0.29	1.98	1.31	2.30	0.86	1.55	2.20
5	6643	4.41	0.06	2.10	1.36	2.38	0.88	1.58	2.34
6	5340	2.23	0.29	2.10	1.33	2.48	0.85	1.61	2.34
7	7122	5.20	0.02	2.20	1.41	2.42	0.91	1.59	2.45
8	6432	4.05	0.12	2.28	1.43	2.55	0.89	1.64	2.55
9	6200	3.67	0.17	2.32	1.41	2.69	0.86	1.69	2.60
10	5800	3.00	0.25	2.36	1.40	2.84	0.83	1.74	2.65
11									
12									
13									
14									
15									
16									
17									
18									
19									
20									
21									

Find the PWD

Figure 3 Second worksheet in the Decision-Support Tool

As in the first worksheet, cells where the user can enter data are highlighted in green. All other cells are for illustrative purposes only. Once the user clicks on the button, the table is populated as the algorithm processes each observation. The observations are downscaled to the feasible range of the PDFs for processing, then rescaled to present the results. The table illustrates the downscaled sample value, the Bayes evidence, or assumed probability, of the sample, the adjusted mean and standard deviation resulting from the sample, and the assumed parameters of the Gamma or Weibull PDF that correspond to the adjusted mean and standard deviation. The values in Row 3 are the downscaled parameters of the design distribution. Therefore, the tabulated data reveals how the adjusted mean, for example, is drawn downward for samples below the design mean, and upward for samples above the design mean. The final parameters of the distribution estimated from the sample are represented along Row 10. Note that any number of observations can be included in a sample. The table is currently set to allow up to 16.

In Figure 3, it is easier to see how the final m.a.p. estimate of the mean is 2.36, which scales up to 5,416. This m.a.p. estimate of the mean is quite different from the mean of the sample lot (6,075), revealing the influence of the design mean (5,200), which was drawn up by the observations.

Once the algorithm is completed, the results are displayed in a chart on a third worksheet, as shown in Figure 4.

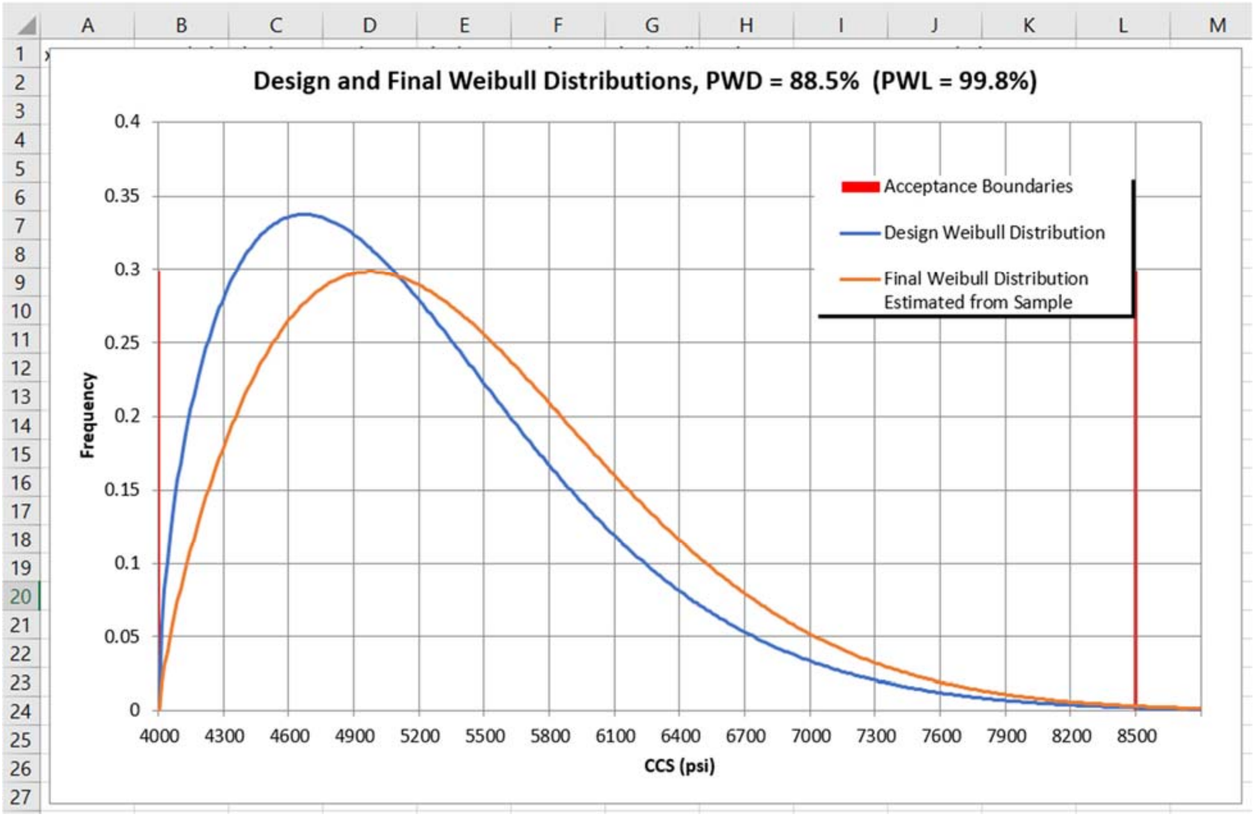

Figure 4 Third and final worksheet in the Decision-Support Tool

The PWD, and the PWL for reference, are both provided in the title of the chart. The interpretation of the PWD is that 88.5% of the area beneath the orange curve between the acceptance boundaries (shown in red) is within the area under the blue curve.

What is also apparent in Figure 4 is the lack of sensitivity of the PWL to reasonably expected sample lots. Recall that this sample lot was randomly selected from a uniform distribution within the acceptance boundaries, so it does not represent observations that are responsive to the design mean. It simply represents a set of observations that ensure the lot is not rejected. In fact, any simulation of this type of random selection yields PWLs at or above 99%.

Processing a second sample through the algorithm [5970 5215 5871 4713 4738 4439 6057] that better mimics the design distribution yields a higher PWD, as shown in Figure 5.

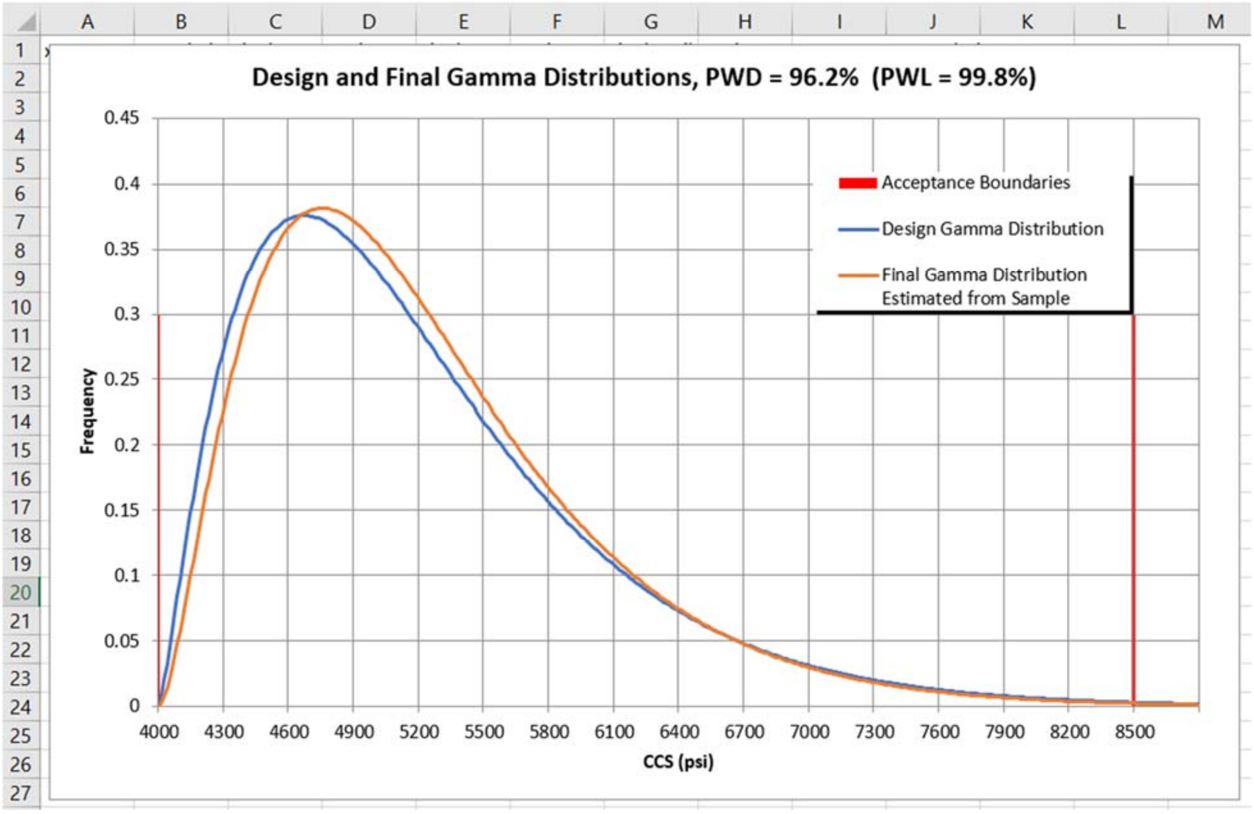

Figure 5 Third worksheet in the Decision-Support Tool after passing through a second sample

Again, the PWL does not provide meaningful information about the sample's adherence to the parameters of the design distribution, but the PWD shows that the contractor has achieved a relatively high degree of adherence to the design distribution, as illustrated by the two curves.

This example illustrates how difficult it will be for sample lots to achieve PWDs at or above 99%. Since the PWD algorithm relies on the use of RVs and an assumption about the industry's knowledge of the design distribution, there is a higher sensitivity in how it is calculated.

For this reason, it is useful to consider what PWDs would result from passing samples through the algorithm that are drawn from the design distribution itself. These samples represent the most desirable observations under a given design distribution, so we would want to design the pay factor schedule so that these samples are rewarded at the maximum pay factor. To determine what these PWDs would be, the decision-support tool code was altered to create a sample simulator, which generates samples as random realizations of a given distribution. The simulator can be used to generate many samples to represent one or more full construction seasons. Using the simulator, 300 randomly-generated samples of 7 observations each for each distribution type (900 simulations total) were passed through the algorithm, and the resulting PWDs and PWLs were recorded. A summary of the results across all 900 simulations is provided in Table 1.

Table 1 Results of applying the algorithm to 300 samples of 7 observations for each design distribution type with a design mean of 5,200 psi and design standard deviation of 800 psi

Distribution Type	Gamma	Gaussian	Weibull
Avg Sample Mean	5,173	5,189	5,257

Avg Sample SD	770	790	833
Avg PWD	95.4%	95.9%	95.8%
25th Percentile PWD	91.3%	91.9%	94.1%
Avg PWL	99.7%	95.8%	99.8%

Of critical importance in these results are two findings. The first is that the PWL continues to show a lack of sensitivity to these samples, averaging 100% across all simulations for two of the three distribution types. The PWLs of the samples generated for the Gaussian distribution have lower PWLs because the Gaussian design distribution already includes a portion of the PDF below the lower acceptance limit. The PWDs are not only more sensitive to the variations in the simulated sample lots but, on average, they are similar regardless of the selected design distribution type. Second, the PWDs for samples generated from the design distribution can be surprisingly low, with the lowest 25th percentiles at around 92%. This means that we have to be careful in designing the pay factor schedule to avoid penalizing sample lots that could be drawn from the design distribution itself. This means that the bottom edge of the range that will receive the highest reward might be as low as 92%. In fact, this simulation can be used to initiate the development of a pay factor schedule. Using these results and assumed values for the peak reward pay factor and a seasonal overpayment amount, we can set a specific set of pay factors that will achieve the desired performance. We can set the maximum pay factor for the range from 92% to 100%, then step down to the next highest pay factor for a range about 4% lower than the bottom of the highest range. In this case, the pay factor for the range from 88% to 92% should still be a reward, since the PWD of 88% is still at the 10th percentile of the sample lots drawn from the design distribution. Below that value, though, we can further reduce the pay factor into values lower than 1.00, penalizing sample lots that do not resemble the design distribution.

In the next section, we set 3 sets of pay factor schedules based on assumed industry responses, using a maximum initial pay factor of 1.06, and an overpayment amount of 3%, with an assumed schedule of initial pay factors that complies with the parameters summarized above, as shown in Table 2.

Table 2 Assumed Initial Pay Factor Schedule for Results Shown in Table 1

PWD Range			Initial Pay Factor	PWD Range			Initial Pay Factor
92%	-	100%	1.06	68%	-	72%	0.88
88%	-	92%	1.03	64%	-	68%	0.85
84%	-	88%	1.00	60%	-	64%	0.82
80%	-	84%	0.97	56%	-	60%	0.79
76%	-	80%	0.94	52%	-	56%	0.76
72%	-	76%	0.91	48%	-	52%	0.73

3.2 Modeling of Industry Response Results

To model the immediate (0-2 years) industry response, we simulate 900 sample lots representing the first few construction seasons, generated through a random selection of values between the lower and upper acceptance range (4,000 – 8,500 psi). A summary of the results of these simulations can be found in Table 3.

Table 3 Results of applying the algorithm to 900 simulated samples for each design distribution type for a random value between 4,000 psi and 8,500 psi

Distribution Type	Gamma	Gaussian	Weibull
Avg Sample Mean	6,278	6,256	6,281
Avg Sample SD	1,270	1,287	1,276
Avg PWD	91.1%	87.9%	91.3%
25th Percentile PWD	89.1%	85.3%	89.4%
Avg PWL	99.0%	93.0%	99.2%

Plugging these simulated sample lots into the pay factor schedule, we get an overpayment of 3%. Therefore, the initial pay factors do not need to be adjusted, as we have met the requirement for overpayment. The calculation of overpayment and the adjusted pay factors are summarized in Table 4.

Table 4 Calculation of overpayment and adjusted pay factors for the results given in Table 3

PWD Range			Initial Pay Factors	N	Initial Unit Payment	Initial Factored Payment	Adjusted Pay Factors	Adjusted Factored Payment
92%	-	100%	1.06	273	$273.00	$289.38	**1.06**	$289.38
88%	-	92%	1.03	379	$379.00	$390.37	**1.03**	$390.37
84%	-	88%	1.00	195	$195.00	$195.00	**1.00**	$195.00
80%	-	84%	0.97	52	$52.00	$50.44	**0.97**	$50.44
76%	-	80%	0.94	1	$1.00	$0.94	**0.94**	$0.94
72%	-	76%	0.91	0	$0.00	$0.00	**0.91**	$0.00
68%	-	72%	0.88	0	$0.00	$0.00	**0.88**	$0.00
64%	-	68%	0.85	0	$0.00	$0.00	**0.85**	$0.00
Sums				900	$900.00	$926.13		$926.13
					Overpayments	**3%**		**3% ✓**

This set of adjusted pay factors can be used in the first few construction seasons, until we expect that the industry has begun to transition. To model the transitionary (2-4 years) industry response, we simulate 900 sample lots representing the 2nd through the 4th construction seasons, generated through a randomized selection of values from the design distribution with the mean at 5,800 psi and the standard deviation at 800 psi. A summary of the results of these simulations can be found in Table 5.

Table 5 Results of applying the algorithm to 300 samples of 7 observations for each design distribution type with a design mean of 5,800 psi and design standard deviation of 800 psi

Distribution Type	Gamma	Gaussian	Weibull
Avg Sample Mean	5,844	5,809	5,848
Avg Sample SD	803	817	1,224
Avg PWD	90.8%	91.9%	93.7%
25th Percentile PWD	88.9%	89.8%	91.8%

Avg PWL	99.6%	94.9%	99.4%

Plugging these simulated sample lots into the pay factor schedule, we get an overpayment of 4%. Adjusting the pay factors, by cutting the peak to 1.04 and reducing the step size to 0.02 to keep line between reward and penalty at 84%, to yield an overpayment of 3% results in the set of adjusted pay factors shown in Table 6.

Table 6 Calculation of overpayment and adjusted pay factors for the results given in Table 5

PWD Range			**Initial Pay Factors**	**N**	**Initial Unit Payment**	**Initial Factored Payment**	**Adjusted Pay Factors**	**Adjusted Factored Payment**
92%	-	100%	1.06	471	$471.00	$499.26	**1.04**	$489.84
88%	-	92%	1.03	337	$337.00	$347.11	**1.02**	$343.74
84%	-	88%	1.00	86	$86.00	$86.00	**1.00**	$86.00
80%	-	84%	0.97	6	$6.00	$5.82	**0.98**	$5.88
76%	-	80%	0.94	0	$0.00	$0.00	**0.96**	$0.00
72%	-	76%	0.91	0	$0.00	$0.00	**0.94**	$0.00
68%	-	72%	0.88	0	$0.00	$0.00	**0.92**	$0.00
64%	-	68%	0.85	0	$0.00	$0.00	**0.90**	$0.00
Sums				900	$900.00	$938.19		$925.46
					Overpayments	**4%**		**3%** ✓

Finally, to model the long-term (4+ years) industry response, we simulate 900 sample lots representing construction seasons beyond the 4th, generated through a randomized selection of values from the design distribution with the mean at 5,500 psi and the standard deviation at 600 psi. A summary of the results of these simulations can be found in Table 7.

Table 7 Results of applying the algorithm to 300 samples of 7 observations for each design distribution type with a design mean of 5,500 psi and design standard deviation of 600 psi

Distribution Type	**Gamma**	**Gaussian**	**Weibull**
Avg Sample Mean	5,508	5,498	5,555
Avg Sample SD	608	620	1,044
Avg PWD	92.1%	94.1%	94.8%
25th Percentile PWD	90.3%	92.7%	93.1%
Avg PWL	99.8%	95.5%	99.7%

Plugging these simulated sample lots into the pay factor schedule, by cutting the peak to 1.03 and reducing the step size to 0.01 to put the line between reward and penalty at 80%, we get an overpayment of 5%. Adjusting the pay factors to yield an overpayment of 3% results in the set of adjusted pay factors shown in Table 8.

Table 8 Calculation of overpayment and adjusted pay factors for the results given in Table 7

PWD Range			Initial Pay Factors	N	Initial Unit Payment	Initial Factored Payment	Adjusted Pay Factors	Adjusted Factored Payment
92%	-	100%	1.06	664	$664.00	$703.84	**1.03**	$683.92
88%	-	92%	1.03	204	$204.00	$210.12	**1.02**	$208.08
84%	-	88%	1.00	32	$32.00	$32.00	**1.01**	$32.32
80%	-	84%	0.97	0	$0.00	$0.00	**1.00**	$0.00
76%	-	80%	0.94	0	$0.00	$0.00	**0.99**	$0.00
72%	-	76%	0.91	0	$0.00	$0.00	**0.98**	$0.00
68%	-	72%	0.88	0	$0.00	$0.00	**0.97**	$0.00
64%	-	68%	0.85	0	$0.00	$0.00	**0.96**	$0.00
Sums				900	$900.00	$945.96		$924.32
					Overpayments	**5%**		**3% ✓**

Chapter 4: Conclusions

The objective of this project was to develop a new quality measure for payment of in-place CCS that does not rely on the assumption of a Gaussian distribution for the industry response and allows for the use of asymmetrical set of pay factors. A new approach was developed, which uses a specified design distribution as the target for pay-factor rewards under a double-bounded performance specification. The new algorithm, called the Percent Within Distribution (PWD), calculates a quality measure from a 28-day CCS lot distribution that is non-Gaussian by comparing it to a design distribution that can be any type (we tested Gamma and Weibull, in addition to Gaussian in this project).

RVs were used to guide the new approach and the simulated responses that the industry would take. We showed how the new quality measure could be used to enforce payment under a double-bounded pay factor schedule, but also how it could be used in a simulation environment to design the pay factor schedule in the absence of complete lifecycle data. The use of the PWD for this purpose was demonstrated by simulating an expected industry response to the new performance specification in the first couple of years, in years 2 through 4, and then beyond the 4th year after the program implementation. Responses by the industry were assumed to evolve from almost no response initially, to a dramatic shift toward the design distribution by the 4th construction season. Table 9 provides a summary of the evolution of the pay factor schedule in the first 4+ years of simulated industry response.

Table 9 Evolution of Pay Factors Under the First 4+ Years of Simulated Industry Response

PWD Range			Pay Factor Schedule		
			Years 0-2	Years 2-4	Year 4+
92%	-	100%	1.06	1.04	1.03
88%	-	92%	1.03	1.02	1.02
84%	-	88%	1.00	1.00	1.01
80%	-	84%	0.97	0.98	1.00
76%	-	80%	0.94	0.96	0.99
72%	-	76%	0.91	0.94	0.98
68%	-	72%	0.88	0.92	0.97
64%	-	68%	0.85	0.90	0.96

The research team also created a decision-support tool to manage the implementation of the new approach. The tool allows the user to specify and visualize their design distribution, then calculate the PWD from a sample lot. The tool is based on MS Excel so that it will useful to DOTs across the country.

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