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Variability in Accuracy Ranges: A Case Study in the US and Canadian Power Industry

John K. Hollmann, PE CCP CEP DRMP FAACE Hon. Life; Don Clark; Krishnamurthy Sastry; Bob Yong Kim; Steven Holmes; William Derrick Allman; Kevin Tong; Carlos Ruiz; Ryan Dixon; Kelman K. Ng, P.Eng.; Dennis R. Raber; Deborah Sapp

Abstract–This paper presents a case study of the variability in accuracy ranges for phased project cost estimates in the North American power industry. The study sought to improve the participants' understanding of risks and estimate accuracy for their major power generation and overhead power transmission projects. The study team also sought to verify the theoretical accuracy values in the relevant AACE International® recommended practices (RPs) for cost estimate classification. The team studied estimated cost by phase (i.e., classification) and final actual data from 40 projects (86 phased estimates) from 6 utility companies completed from 2008 to 2019 with actual costs from 7 million to 771 million (2019$US). Schedule data was also studied, but is not the focus of this paper. Greenfield and brownfield power generation and transmission projects from across the US and Canada were included. Comparisons of the findings is made with other published studies. This study used the same approach as (and general text is intentionally similar to) two Canadian hydropower and overhead power transmission accuracy studies presented at AACE conferences in 2014 and 2017.

Table of Contents

Introduction

Accuracy is a measure of how a cost estimate differs from the final actual outcome. Risk analysis provides forecasts of how the final actual outcome may differ from the estimate (such as a base estimate or an amount approved for expenditure). Historical analysis helps to understand the variability of accuracy and to improve risk analysis practice, particularly in respect to parametric modeling of systemic risks [1]. This study is such an historical analysis.

Empirical estimate accuracy data has been researched for over 50 years [2]. In particular, the accuracy of process industry project estimates (e.g., oil and gas, chemical, mining, etc.) has been well documented. Other studies have highlighted industry bias and misperceptions of the reality of estimate accuracy [3]. However, in 2014 there was a relative void in accuracy studies for power generation and transmission projects. Two studies of the accuracy of estimates were conducted by the Canadian power industry to help fill that gap [4,5]. This study extends that research to US power generation and transmission projects (plus additional Canadian projects); the analytic methods used (and the structure of this paper) for the three studies were essentially the same.

One catalyst, and point of comparison, for these utility studies was the development by the Construction Industry Institute® (CII) of a Project Definition Rating Index (PDRI) for "infrastructure" projects in 2011 [6]. CII defined infrastructure as providing "transportation, transmission, distribution, collection or other capabilities" that usually impact multiple jurisdictions and stakeholders across a wide area. CII characterized infrastructure as scope including "nodes and vectors". In that respect, this study covers both the power generation and substation "nodes" as well as the transmission "vectors". It was hypothesized that while nodal projects would likely have similar accuracy characteristics to process plants, vector projects were more likely to experience unique and increasing regulatory risks with their cross-jurisdiction and varied (and sometimes sensitive) environments nature.

This study was also needed to help verify the applicability of the theoretical range-of-range accuracy values in the AACE® "Cost Estimate Classification System" RPs for the process (i.e., generation) and power transmission industries [7,8]. The participants of this study sought to provide their respective utility commissions a high quality, statistically significant study that demonstrates the prudency and reasonableness of AACE® RP-based utility estimates and contingencies.

The questions in regard to those RPs were "do the ranges in these RPs reflect real accuracy ranges?" and if not, "how can one assure that the values shared in the RPs do not inappropriately bias stakeholder expectations and risk analyst practice?".

Background

The study team included project, engineering and capital community representatives from six US and Canadian utility companies; the team members are listed as co-authors. PG&E and Duke Energy had a key role in facilitating study data collection and reviews. The team collected estimated and actual project capital cost data from 40 recent projects from 10 US states and 1 Canadian province with actual costs from $7 million to $771 million (average $161M in 2019 $US) completed from 2008 to 2019. 17 of the projects were of generation scope and 23 were transmission.

A primary goal was to study the cost and schedule accuracy versus level of scope definition as measured by estimate classification. Therefore, cost and schedule estimate data from each scope development phase (decision gates) was captured. 86 cost estimates were captured for the 40 projects; most projects reported more than one phased estimate. The number of cost estimates by estimate class, size ($22M roughly divides small versus large projects; this is escalation from prior studies that used $20M) and type is shown in Table 1:

Estimate Count	Class 2	Class 3	Class 4	Class 5
Total	10	29	29	17
<=$22M	1	6	5	3
>$22M	9	23	24	14
Generation	4	12	10	5
Transmission	6	17	19	12

Table 1–Number of Cost Estimates Studied by Class, Size and Type

The generation project scopes included steam, gas turbine, wind and solar. Transmission excludes local distribution. The project types varied from greenfield to revamp. To minimize bias, the dataset represented all the recent major project data available to the participants regardless of whether the project cost outcome met company cost and schedule objectives.

Analysis Approach

The primary analytical methods used were descriptive statistics. The accuracy metric described by the statistics and the dependent variable of regression was the ratio of “base estimate/actual” for cost and schedule. “Base estimates” of each Class exclude contingency and management reserves, and interest and escalation for cost. This was done because the team wanted to understand how actual costs and duration differed from the base estimate so that they could improve future predictions of this difference (i.e., to be able to forecast the contingency required).

The cost represents capitalized cost, which is usually cost incurred from the point of selecting a single scope option (of whatever Class) through mechanical completion and start-up (costs are usually expensed prior to and after this period). The schedule duration represents *execution* which is usually measured from the date of full funds sanction and start of detailed engineering through mechanical completion.

No information was collected on the quality of the base estimates. Given the cross section of companies and variety of project types, it is assumed that the base estimate quality is highly variable, but the average is likely representative for the industry group. A source of uncertainty that was not measured, but influences accuracy results, is the common industry practice of including *growth allowance* in the base estimate. 5 to 20% embedded growth allowances are not unusual, particularly for early estimates. Per AACE RP 10S-90 allowance definition [9], this and other general, non-specific allowances belong in contingency, not the base. No corrections were made for this practice in this study; however, users should be aware that if their base estimates *exclude* gross allowances above-the-line (as is recommended), more contingency may be required than is indicated by the average cost growth metrics reported here.

The estimate/actual ratio format was used because this metric tends to be relatively normally distributed and is hence amenable to multiple linear regression analysis [10]. As will be discussed later, the more commonly considered actual/estimate (inverse of estimate/actual) tends to be biased to the high side which is problematic for regression analysis (the lognormal distribution is usually a good fit for actual/estimate so regression of actual/estimate logarithms is an option).

The independent variables or project characteristics studied (estimate/actual being the dependent variable) included:

- Scope definition behind estimate (i.e., AACE® Class 2, 3, 4 or 5)
- State/Province
- Proximity to populated areas
- Cost/Schedule Strategy (i.e., cost or schedule driven)
- Terrain/Site Conditions/Weather
- New Technology or Scale
- System Complexity
- Execution Complexity
- Primary Project Type (e.g., greenfield, revamp, etc.)
- Primary Construction Contract Type
- Owner PM System Maturity
- Indigenous Stakeholders Engagement / Involvement
- Environmental Sensitivity of Land/ROW

Also, the cost content of each project in terms of percent of cost for equipment, construction, and so on was captured. To collect the data a form was used that captured the following:

- General project characteristics
- High level “base” cost estimate breakdowns at each AACE® Class plus contingency and escalation cost estimates for each
- Actual final cost

- Key planned and actual schedule milestones
- Scope change and risk event information

The actual cost data was normalized to the year of the respective estimate using the mid-point of spending approach (actual project cash flows were not available) [11]. The normalization price index used was the Chemical Engineering Plant Cost Index [12]. Also, cost and duration changes due to business scope change were adjusted out (costs resulting from a change to a basic premise of the estimate such as capacity, etc.). Such corrections were minimal; none of the projects were observed to have experienced a catastrophic risk event.

The primary variable (uncertainty or risk driver) of interest was the level of scope definition upon which the estimate was based. Not all projects had data for estimates of each AACE® Class as can be seen in Table 1. An unusual characteristic of this dataset was that many projects were sanctioned based on Class 2 estimates (i.e., based on tenders) and for which no Class 3 estimate (the usual basis of sanction) was prepared. Also, there were relatively few Class 5 observations; the origin of early budget values is often unclear. Only 13 projects reported a three-step or gate estimate progression (usually Class 5,4,3) indicating likely better phase-gate process discipline being applied than on the other 27 projects.

A dataset of 40 observations is considered an adequate sample size to gain useful insight as to the relationship of accuracy and estimate class, and to provide some limited understanding of the impact on accuracy of more dominant uncertainty drivers such as external regulatory risks. Note that some of the data point counts may add to less than the total projects or estimates because of missing detail data for some of the inputs.

Findings for Accuracy Range by Class: Descriptive Statistics

This section shows the dataset statistics for accuracy using “p-values”. The p-value (e.g., p50) is the level of confidence expressed as a percentage of sample values that will be less than that shown. The p-values are calculated using the Excel® “Norminv” function applied to the base estimate/actual data, and then converted to the traditional actual/base estimate ratio format. This method of inferring the population distribution from a sample is consistent with the method described in AACE RP 42R-08 and is supported by process industry research that indicates that estimate/actual data (as opposed to its inverse of actual/estimate) is more or less normally distributed [1]. This reasonable inference smooths the choppier data of small samples.

Table 2 shows the accuracy metrics by estimate classification for the projects in this study. It shows the amount of contingency that would need to be added to the base estimate in order for funding to predict the actual. For example, for Class 5, the p50 value of 1.28 means that 28% contingency would need to be added to a Class 5 base estimate to achieve a 50 percent confidence of underrunning (for 90 percent confidence, the corresponding contingency or reserve would be 144%!). Figure 1 depicts a log-normal fit for the accuracy data in Table 2.

Actual/Base Estimate	Class 2	Class 3	Class 4	Class 5
number of observations	*10*	*29*	*29*	*17*
Mean	1.11	1.02	1.24	1.28
p90	1.28	1.40	1.91	2.44
p50	1.11	1.02	1.24	1.28
p10	0.98	0.81	0.92	0.87

Table 2–Dataset Cost Estimate Accuracy Metrics (Actual/Base Estimate)

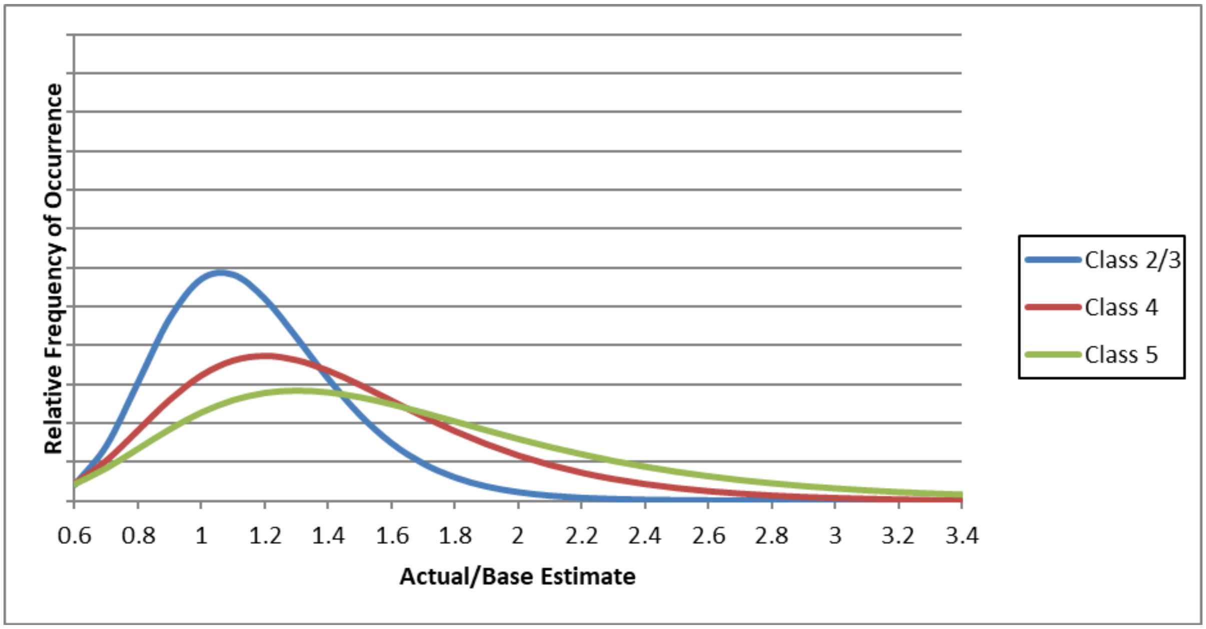

Figure 1–Accuracy Metrics Fitted to Lognormal Distributions

Note the high side skewing in Table 2 and Figure 1. For example, the Class 4 p90 of 1.91 is much further from the mean than the p10 value of 0.92. Arguably, the p90 (or practical worst case) value is more important to investment decisions, considering sensitivity analysis, than the mean or p50. It is also important to recall that these metrics exclude the impact of escalation and major business scope change.

Table 2 and Figure 1 include all of the estimates in this study. Table 3 shows the accuracy metrics for only the 13 projects that applied a three-step (or gate) estimate progression indicating possibly greater discipline being applied in phase-gate processes. The three step values display a steadier, more linear progression in cost growth versus estimate class. For projects with two-stepped estimates, it is likely that the level of scope definition was less well aligned with AACE classification standards. For example, with two steps, it is likely the early estimate was somewhere between Class 5 and 4 and the next between 4 and 3 (or even 2). Figure 2 depicts a log-normal fit for the accuracy data for the 13 projects in the dataset that had a full three step progression. The Y-axis gridlines of Figures 1 and 2 were set to be the same so that one can see the stronger central tendency of the three-step sample.

Actual/Base Estimate	Class 2/3	Class 4	Class 5
Mean	1.06	1.16	1.38
p90	1.25	1.74	2.38
p50	1.06	1.16	1.38
p10	0.92	0.87	0.97

Table 3–Accuracy for the 13 Projects with Three Phased Estimates

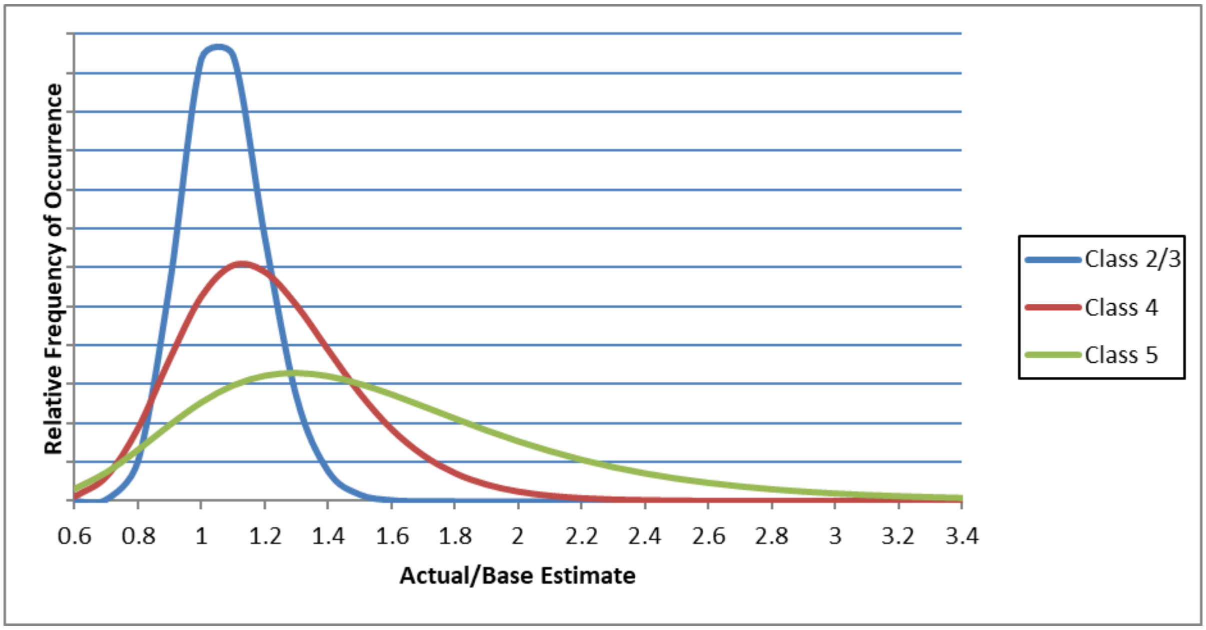

Figure 2–Three-Step Cost Growth (13 Projects) Fitted to Lognormal Distributions

Effect of Project Size

Industry research indicates that there is a dichotomy between how small versus large projects are managed and estimated [3]. Small projects tend to be managed as a portfolio with project team members having responsibility for multiple projects using less disciplined management procedures. Large projects usually have dedicated teams and more disciplined procedures. The focus of small project funding tends to be on overall portfolio budget predictability which translates to a bias towards over-estimation of the base for an individual project, spending the full project budget, and if overruns become excessive, sometimes finishing the scope on another project (or similar less disciplined practices) in the somewhat fluid small project portfolio. Table 4 shows the ranges for small versus large projects (less or more than US2019$22 million).

Actual/Base Estimate	Class 3		Class 4		Class 5	
$2019M	<=22M	>22M	<=22M	>22M	<=22M	>22M
p90	1.31	1.42	1.60	1.99	2.62	2.48
p50	1.04	1.02	1.23	1.24	1.34	1.27
p10	0.87	0.79	1.00	0.90	0.90	0.85

Table 4–Cost Estimate Accuracy by Class and Project Cost Range

For this dataset, the p50 values of small and large projects are similar; i.e., size was not a driver of uncertainty at the mean. The small project ranges look narrower at Class 3 and 4 which may imply overestimation to hit the budget. However, only 6 of the 40 projects with Class 3 estimates were <$22M; the differences are not statistically significant for this dataset.

Differences Between Generation and Transmission Projects

Table 5 shows the ranges for generation and transmission projects. The average size of the generation projects is greater than for transmission ($242M vs. $102M), but both are large projects on average and should reflect similar project cultures (i.e., size is likely not a driver). There is considerable variability in the statistics for the small asset type sub-set samples. However, the range variations are similar for generation and transmission. The p90 values for both generation and transmission increase from about 1.3 to 2.5 (i.e., +30 to +150% cost growth) from Class 2 to Class 5, while the p10 values are relatively constant for all classes at about 0.90 (i.e., -10%). While the differences between the mean values at each estimate class are not statistically significant, this may reflect a balancing of inherent and external risks (e.g., generation may be inherently more complex, but transmission may be subject to greater external risk such as environmental sensitivity).

	Class 2	Class 3	Class 4	Class 5
Generation	*4*	*12*	*10*	*5*
Mean	1.07	1.04	1.20	1.34
p90	1.26	1.19	1.68	2.62
p50	1.07	1.04	1.20	1.34
p10	0.93	0.92	0.93	0.90
Transmission	*6*	*17*	*19*	*12*
Mean	1.14	1.01	1.26	1.26
p90	1.30	1.52	2.08	2.46
p50	1.14	1.01	1.26	1.26
p10	1.02	0.76	0.91	0.85

Table 4–Cost Estimate Accuracy by Class and Asset Type

Comparison to AACE International Ranges

Table 6 compares the AACE expected accuracy ranges from RPs 96R-18 and 18R-97 [7,8] to the study ranges in Table 2 using the percentage differences of p10/p90 values from the p50 values (the presumed funded amount upon which the AACE metrics are based). For this dataset, the study ranges are similar to the AACE highest and lowest extremes; for example, the widest *expected* Class 3 range in the AACE RPs is +30/-20% while this study's range was +37/-21%.

ESTIMATE CLASS	RP EXPECTED ACCURACY RANGE Typical variation in low and high ranges at an 80% confidence interval	STUDY RANGES
Class 5	L: -20% to -50% H: +30% to +100%	L: -32% H: +90%
Class 4	L: -15% to -30% H: +20% to +50%	L: -26% H: +54%
Class 3	L: -10% to -20% H: +10% to +30%	L: -21% H: +37%
Class 2	L: -3% to -10% H: +3% to +15%	L: -12% H: +15%

Table 6–Accuracy Ranges from AACE RPs and This Study

The project phase-gate process documentation of most companies quotes *expected* or target ranges that are usually near the midpoint of the AACE RP range-of-ranges [2]. For example, for Class 5, 4 and 3, the typical company p90/p10 range expectations or policy may be stated as +50/-30, +30/-20 and +20/-15% respectively. As can be seen, the actual p90 ranges are close to the worst expectation which is about 2 times the typical expectations and 3 times the optimistic expectation. This and other studies [2] provide no grounds for such optimism.

Comparison of Cost Contingency Estimates to Actual Cost Growth

Excluding one outlier, the project estimates in this study allowed an average of 12% contingency with a standard deviation of +/-6% and min/max range from 2 to 32%. A nearly constant contingency allowance was applied for all classes of estimates! The average contingencies allowed for Class 2, 3, 4 and 5 were 14%, 10%, 11% and 16% respectively. Only 4 or the 79 estimates of any class allowed for contingencies >25%. There appears to be little recognition that the level of scope definition has a strong influence on cost uncertainty (or if it is recognized, it is administratively not being allowed for). Compared to the actual cost growth at p50 in Tables 2 or 3, the average contingency allowed for Class 2 and 3 is about twice what is needed, but about half what is needed for Class 4 and 5. Like a broken clock, constant contingency estimates will sometimes be correct. Figure 3 shows the frequency of contingencies being allowed with the most likely range of all classes being 10 to 15%.

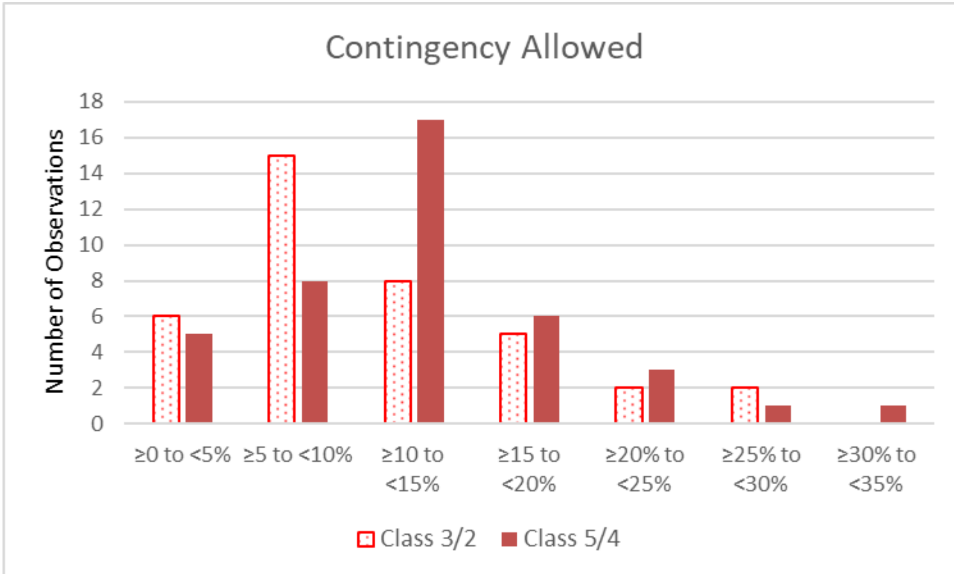

Figure 3–Contingency Being Allowed by Class

Assuming these projects used probabilistic risk analyses (at least at face value), near constant contingency at p50 implies near constant worst case values were also reported and presumably used in profitability or similar sensitivity analyses for decision making. Near constant ranges means that the risk analyses are largely irrelevant to project sanction decisions; i.e., they do not provide information that distinguishes between alternatives. This is particularly concerning for Class 4 estimates which are used for alternative selection. Figure 4 highlights the discrepancy between estimated and actual accuracy range for Class 4. This may be a by-product of mandated utility infrastructure requirements and utility profitability regulations.

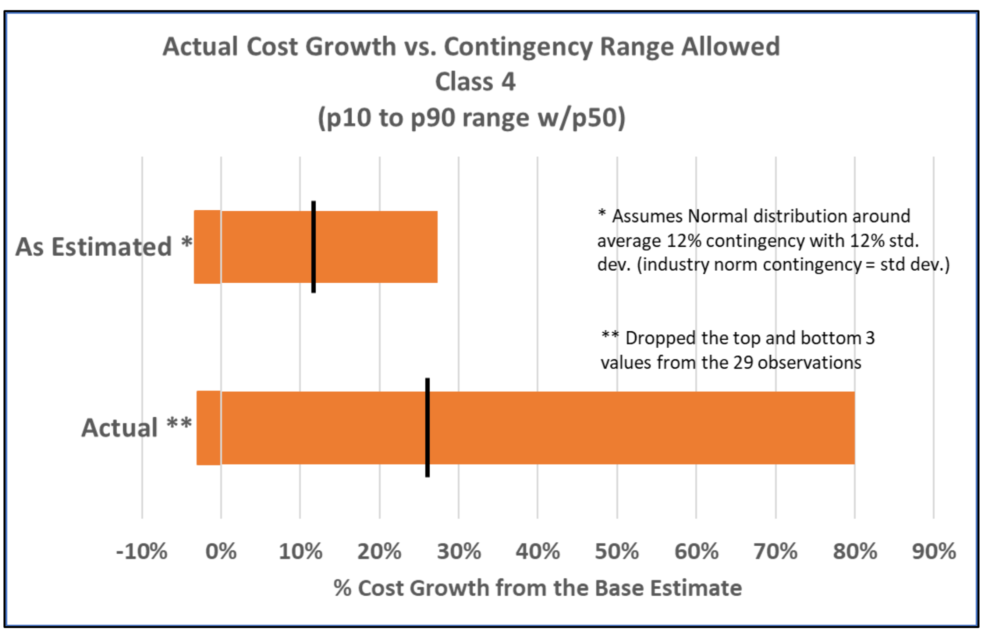

Figure 4–Estimated vs. Actual Cost Growth for Class 4 Estimates

Combined Study Outcome

As was mentioned, two prior Canadian utility studies published in AACE Transactions (4,5) used the same analytic methods and were facilitated by the same party. The datasets were combined for limited analysis. The combined dataset included 89 projects and 214 estimates. Table 7 summarizes the combined accuracy statistics. The larger dataset smoothed out the results so that the increase in accuracy from Class 5 to Class 3 is more evident than was true for the smaller individual samples. Figure 5 depicts a log-normal fit for the accuracy data in Table 7.

Actual/Base Estimate	Class 2/3	Class 4	Class 5
number of observations	*89*	*71*	*54*
Mean	1.10	1.27	1.42
p90	1.55	2.11	2.77
p50	1.10	1.27	1.42
p10	0.85	0.91	0.95

Table 7–Accuracy Ranges from Combined Utility Studies (Actual/Base Estimate)

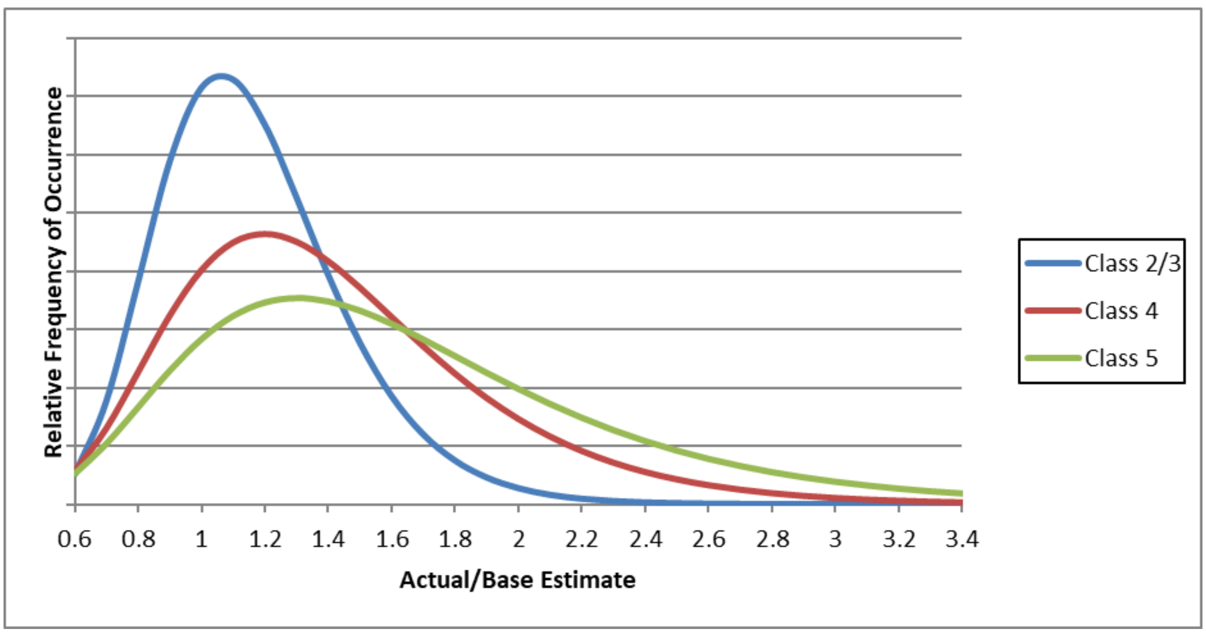

Figure 5–Accuracy Metrics Fitted to Lognormal Distributions: Combined Studies

Comparison of Findings to Other Studies and AACE RP18R-97

Statistically speaking, considering sample sizes, data quality, and estimate class rating assumptions, this study's accuracy ranges are roughly comparable to those reported for empirical studies of similar processes and infrastructure. All the studies show values near or beyond the extremes of the RP 18R-97 and 96R-18 ranges. Table 8 summarizes the study result comparison.

A difficulty in such comparisons is ascribing an estimate class rating to historical projects. In the author's experience, few estimates are truly based on the scope deliverable status required by AACE for a Class 3 sanction estimate. For example, RP 18R-97 calls for P&IDs, both process and utility, to be issued-for-design at Class 3; however, this is rarely achieved. Experiences shows that most estimates labeled as Class 3 are actually based on definition somewhere between Class 3 and 4. This is most apparent in the tighter ranges seen in the IPA, Inc. (Ogilvie, et.al. [13]) reference in Table 8. IPA's benchmarking process assures appropriate rating of scope definition (i.e., IPA's FEL 3 is AACE Class 3) and better data quality in general. This was also seen in the tighter ranges for the 13 projects in this study that reported three-step phased estimating (Table 3).

Note that this study's Table 2 values were adjusted to reflect the accuracy relative to the estimate *including contingency* (i.e., the funded or sanctioned amount) which is typically what is reported in published studies because historical records do not capture base estimate values; only authorized totals. The contingencies added to this study's Class 2, 3, 4 and 5 base estimates were 8%, 10%, 12% and 15% respectively which correspond to typical contingency allowances seen in industry.

Of particular note is the consistency of the very high p90 values in the actual data. For decision making, particularly when selecting a single alternative at Class 4, it is the p90 value that differentiates alternative risk profiles. The p90 values for Class 4 estimates in these studies ranges from +60 to +100% over the funded amount (and 130 to 200% for Class 5). This is 2 to 3 times the p90 values that are seen in typical project risk analyses.

Combined: US & Canadian	**Class 2**	**Class 3**	**Class 4**	**Class 5**
p90		45%	99%	162%
p50		0%	15%	27%
p10		-25%	-21%	-20%
This Study-Transmission	**Class 2**	**Class 3**	**Class 4**	**Class 5**
p90	22%	42%	96%	131%
p50	6%	-9%	14%	11%
p10	-6%	-34%	-21%	-30%
This Study-Generation				
p90	18%	9%	56%	147%
p50	-1%	-6%	8%	19%
p10	-15%	-18%	-19%	-25%
Canadian-Transmission [5]				
p90		54%	122%	151%
p50		-2%	12%	23%
p10		-29%	-28%	-22%
Canadian-Hydro Generation [4]				
p90		53%	97%	186%
p50		14%	28%	64%
p10		-11%	-6%	12%
IPA Inc., Process Industry [13]; p10/p90 approximated from histogram illustration				
p90		40%	70%	200%
p50		1%	5%	38%
p10		-15%	-15%	-15%
Hollmann, Process Industry [2]; meta-analysis (sanction assumed between Class 3/4)				
p90			70%	
p50			21%	
p10			-9%	
Merrow, Hydro [14]; Mean & Std Dev Reported; Normal distr assumed (sanction Class 3/4)				
p90 (assuming normal)			65%	
Mean			24%	
p10 (assuming normal)			-17%	
CII Infrastructure PDRI [6] data from Figure 6.6; mean PDRI <200: Class 2/3				
p90 (assuming normal)		30%		
Mean		6%		
p10 (assuming normal)		-11%		
AACE RP 18R-97 and 96R-18				
p90	+3 to +15%	+10 to +30%	+20 to +50%	+30 to +100%
p10	-3 to -10%	-10 to -20%	-15 to -30%	-20 to -50%

Table 8–Comparison of Studies (Percent Overrun of Estimate including Contingency)

Regression Analysis of Cost Growth Uncertainty

The study included multi-variable regression modeling of the impacts of project attributes (i.e., systemic risks) on cost growth. All the attribute variables collected (see prior bullet list) were studied. With a dataset of 40 projects, one cannot expect to find more than 3 or 4 independent variables with statistically significant correlation to the dependent variable (i.e., typically 10 or more varied observations are needed for each independent variable).

Regression was done using several datasets. The first included each estimate as a unique record (85 good observations) in order to examine the impact of the level of scope definition (i.e., Class) at the time of the estimate. In addition, regressions were done for separate Class 5, 4 and 3/2 (i.e., sanction) datasets to compare to the all-estimate regression.

Each independent variable (risk driver) was tested alone and in various transformations (e.g., power function of size or a rating value) and combinations. While the detailed findings from the modeling are confidential, the primary finding of the modeling that can be shared is that, as expected, the level of scope definition (estimate class) is the most statistically significant driver of uncertainty. The impact of estimate class is also well demonstrated in the descriptive metrics shared in this paper.

In addition to estimate class, three other variables were shown to be statistically significant drivers of uncertainty for the all-estimate dataset as well as the Class 4 and 3 specific datasets (significance for this study meant that the probability that the model relationship was random was less than 5%). Those drivers include:

- Terrain/Site Conditions/Weather (more unfavorable; more uncertain)
- Indigenous Stakeholders Engagement / Involvement (more involvement; more uncertain)
- Environmental Sensitivity of Land / ROW (more sensitivity: more uncertain)

Because of multi-collinearity, these three were combined into a single weighted contingent risk variable in the model. The conditions variable was weighted at twice the others. Contingent means these attributes are neither systemic in nature (i.e., are not an artifact of the project system) or inherent to the asset type. As ex-poste ratings, these likely reflect awareness that a project had experienced challenging risk events and conditions such as regulatory agency actions, protests, and so on. These risks are not expected to be included in competitive base estimates, but certainly should be quantified in project risk analyses.

The combined variable above was statistically significant but the regression R-squared was only about 0.2 (i.e., the model explains only about 20% of the variance). The fact that other attribute variables (e.g., project type, size, complexity, etc.) did not show up as being statistically significant does not mean they are unimportant. A larger, more varied (e.g., projects with greater range of complexity) sample of projects might result in different conclusions and a stronger model.

Conclusion

This study suggests that the actual cost uncertainty, for the projects studied, is about the same as the “worst case” theoretical accuracy range-of-ranges in AACE RPs 18R-97 and 96R-18. For example, the p10/p90 bandwidth for the study projects for Class 3, 4 and 5 was 58, 80 and 122 percent respectively versus 50, 80 and 150 for the AACE RPs (see Table 6).

On the other hand, the actual contingencies being allowed for were essentially constant for all class estimates (about 12 percent). The average contingencies allowed for Class 3, 4 and 5 were 14, 10 and 16 percent respectively versus 10, 27 and 42 percent needed (see Table 7 and Figure 4). There is great opportunity for these companies (and industry as a whole) to improve the quantification of uncertainty for Class 4 and 5 estimates.

In addition to the level of scope definition, several other drivers of uncertainty were identified. These include terrain/site conditions/weather, indigenous stakeholder's involvement, environmental sensitivity of land, asset type, and equipment cost as percent of total.

Overall, the power projects in this dataset had similar cost growth to that observed in other studies of the process and infrastructure industries.

It is hoped that the findings of this study will add to the participant's and industry's understanding of the importance of the level of scope definition to cost growth, and to increase appreciation of the AACE International estimate classification RPs. The participants also gained parametric models of cost growth and schedule slip for their internal use. It is also hoped that this study will encourage others to conduct empirical risk analysis research of their own cost and schedule data.

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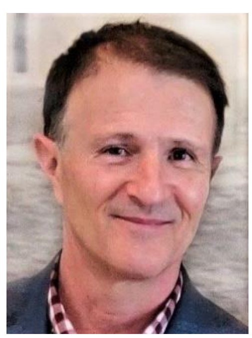
John K. Hollmann, PE CCP CEP DRMP FAACE Hon. Life
Validation Estimating LLC
jhollmann@validest.com



Don Clark
Pacific Gas and Electric Company

Krishnamurthy Sastry
Pacific Gas and Electric Company
k6sz@pge.com

Bob Yong Kim
Pacific Gas and Electric Company
byk1@pge.com

Steven Holmes
Duke Energy Corporation, LLC
stevejholmes@yahoo.com

William Derrick Allman
Duke Energy Corporation, LLC

Kevin Tong
BC HYDRO
kevin.tong@bchydro.com

Carlos Ruiz
Entergy Services, Inc.
cruiz@entergy.com

Ryan Dixon
Entergy Services, Inc.
rdixon3@entergy.com

Kelman K. Ng, P.Eng.
BC HYDRO
kelman.ng@bchydro.com

Dennis R. Raber
Arizona Public Service

Deborah Sapp
Arizona Public Service