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COMPARING CRYSTAL BALL® WITH ACEIT

By Dr. Shu-Ping Hu and Alfred Smith
Tecolote Research Inc.
5266 Hollister Ave. No 301
Santa Barbara, CA 93111

ABSTRACT

There are a variety of methods used throughout the DoD cost analysis community to quantify and calculate the risk inherent in a government project cost estimate. Crystal Ball is a popular application that is in wide use across DoD. The DoD has also sponsored its own application Automated Cost Estimating Integrated Tools (ACEIT www.aceit.com) is an automated architecture and framework for cost estimating. ACEIT is a government developed tool that has been used for over a decade to standardize and simplify the Life Cycle Cost estimating process in the government environment. We often get questions from the field asking why Crystal Ball results do not "match" those from ACEIT. Almost always, we have traced these problems to either confusion on terminology, differences in default settings and/or modeling technique inconsistencies.

A specific concern to military cost analysts is the manner in which correlation is dealt with in a risk simulation. Crystal Ball employs Spearman Rank correlation and ACEIT uses Pearson Product Moment. To test correlation and other cost risk analysis issues, we modeled several case studies published by leaders in the profession. We were careful to pick case studies that have published analytical results for representative cost models. We compared the analytical results to results generated by Crystal Ball and ACEIT to demonstrate that if key modeling decisions are made consistently across the models, the results match well.

1 BACKGROUND

DoD develops cost point estimates through a systematic process of defining (work breakdown structures) the project, populating it with cost estimating relationships (CERs) and the application of risk. To be sure there are a multitude of other influences built into the cost model such as inflation, phasing, learning and labor rate burdens. However, at the heart of it all are technical inputs driving (often parametric) CERs. There is risk in the input variables (configuration risk), risk in the CERs (cost risk), schedule/technical risk implications and risk distribution correlation to be considered.

Having developed Microsoft® Excel based cost estimating models, many military cost analysts will turn to Crystal Ball to layer risk assumptions on their estimate. Many other military analysts will use ACEIT to do the work. Often, analysts will wonder why the tools do not produce identical answers. This paper serves to demonstrate that if care is taken, they almost always will produce the same answers.

A literature search was conducted to identify suitable, published case study examples where the risk results are solved analytically. Two case studies are studied in this paper: Case Study Page CE V – 80 SCEA Training Manual (Reference 1) and MCR Hand Calculator Case Study (Reference 2).

2 ANALYSIS RESULTS

We selected the Latin Hypercube method (LHC) using ten thousand (10,000) iterations to analyze all the test cases. Five thousand (5000) was chosen as the sample size for the Latin Hypercube intervals in Crystal Ball (CB) because it is the upper bound in CB. According to the default assumption given by ACE and @Risk, the number of LHC bins is the same as the number of iterations that are executed during the simulation process. So 10K is also the LHC sample size for both ACE and @Risk.

In ACE, we can control the random seed for every risk assumption, while in CB and @Risk we can only control the very first one. Since 3320 was the first random seed that ACE generated for our risk session, we used this number as the initial seed for both CB and @Risk test cases in an effort to be consistent.

3 CASE STUDY PAGE CE V – 80 SCEA TRAINING MANUAL

This small case study has 11 child WBS elements as published. One of the elements was assigned an "additive" risk term, and for convenience, we broke that element into two: one for the CER and one for the additive risk.

Five of the WBS elements are each estimated as a factor of the Prime Mission Product (PMP). The PMP plus these five elements constitute about 70% of the total point estimate. Since the normal distribution applied to PMP flows through 70% of the estimate, it is reasonable to assume the Electronic System risk will be normally distributed. Table 1 provides the details of the cost model and compares the published, analytically derived standard deviations (Sd) to the standard deviations from the simulation models. The model is somewhat unrealistic because there is no attempt to put risk on the factor relationship.

Table 1: SCEA Case Study

	Equation/ Throughput	Distrn	Lower	Point Estimate	Upper	Sd	ACE Stdev	CB Stdev	@Risk Stdev
Electronic System						6.015	6.013	6.026	5.998
PMP	12.50	Normal		12.500		2.569	2.570	2.569	2.569
SEPM	0.5*PMP			6.250		1.285	1.285	1.284	1.285
Sys Test & Evaluation				4.706		0.811	0.811	0.812	0.809
Sys Test & Eval	0.3125*PMP			3.906		0.803	0.803	0.803	0.803
Management Reserve	0.80	Uniform	0.6	0.800	1.0	0.115	0.116	0.115	0.115
Data and Tech Orders	0.1*PMP			1.250		0.257	0.257	0.257	0.257
Site Survey & Activation	6.60	Tiangular	5.1	6.600	12.1	1.505	1.505	1.505	1.505
Initial Spares	0.1*PMP			1.250		0.257	0.257	0.257	0.257
System Warranty	1.10	Uniform	0.9	1.100	1.3	0.115	0.116	0.115	0.115
Early Prototype Phase	1.50	Triangular	1.0	1.500	2.4	0.290	0.290	0.290	0.290
Operations Supt	1.20	Triangular	0.9	1.200	1.6	0.143	0.143	0.143	0.143
System Training	0.25*PMP			3.125		0.642	0.643	0.642	0.642

In this case study, the risk statistics (means, standard deviations, percentiles, etc.) generated by ACE, CB, and @Risk were very close to one another; the percentage differences all within half a percent. The analytic results were derived based on the assumption the risk at the total level was normally distributed. The simulation results (except for FRISK) matched the analytically derived percentile results very closely as shown in Figure 1. Crystal Ball and ACE seemed to be slightly closer to the analytical results than @Risk.

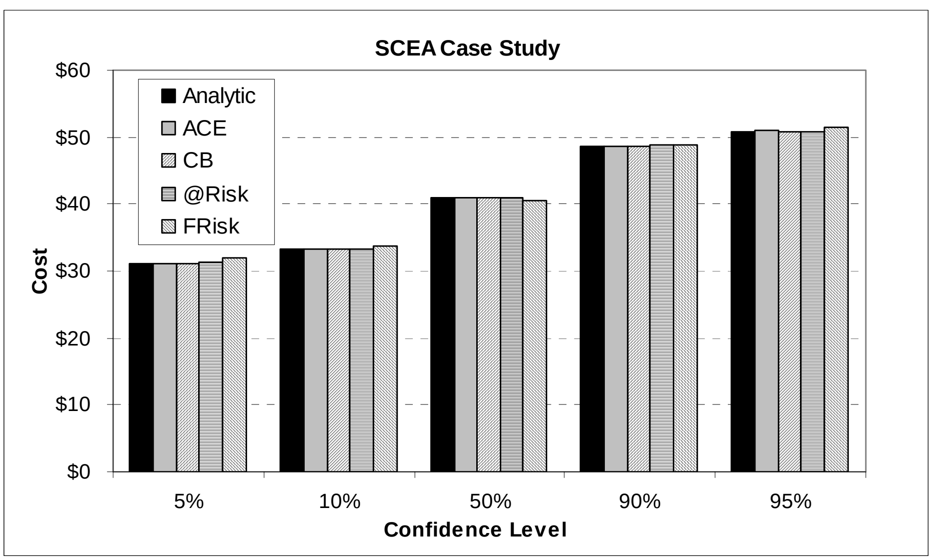

Figure 1: Compare risk simulation tools risks based upon 10K iterations.

4 HAND CALCULATOR CASE STUDY

Here, System X was composed of nine WBS elements. Unlike the SCEA case study, this one contains no CERs. The estimate is comprised of merely nine throughput numbers. These elements were assigned triangular distributions with various dispersion and skewness measures, and they were also correlated. The following two tables identify the triangular distributions and the corresponding correlation assumptions. The means and standard deviations were calculated analytically based upon the triangular distributions and the correlation matrix.

Table 2: MCR Case Study

	Point Estimate	**Lower**	**Mode**	**Upper**	**Mean**	**Standard Dev**
System X	1250	625		3393	1756	491.78
Antenna	380	191	380	1151	574	207.62
Electronics	192	96	192	582	290	105.08
Structure	76	33	76	143	84	22.63
LV Adaptor	18	9	18	27	18	3.67
Power Distrn	154	77	154	465	232	83.86
ACS/RCS	58	30	58	86	58	11.43
Thermal Control	22	11	22	66	33	11.88
TT&C	120	58	120	182	120	25.31
Software	230	120	230	691	347	123.68

Table 3: MCR Case Study Correlation Matrix

Correlation Matrix	Antenna	Electronics	Structure	LVAdaptor	PowDistr	ACSRCS	Thermal	TTC	Software
Antenna	1.0	0.5	0.5	0.6	0.5	0.5	0.3	0.7	0.7
Electronics	0.5	1.0	0.4	0.5	0.5	0.6	0.5	0.5	0.7
Structure	0.5	0.4	1.0	0.7	0.6	0.7	0.7	0.5	0.7
LVAdaptor	0.6	0.5	0.7	1.0	0.4	0.4	0.5	0.3	0.6
PowDistr	0.5	0.5	0.6	0.4	1.0	0.5	0.5	0.5	0.7
ACSRCS	0.5	0.6	0.7	0.4	0.5	1.0	0.4	0.7	0.8
Thermal	0.3	0.5	0.7	0.5	0.5	0.4	1.0	0.5	0.7
TTC	0.7	0.5	0.5	0.3	0.5	0.7	0.5	1.0	0.8
Software	0.7	0.7	0.7	0.6	0.7	0.8	0.7	0.8	1.0

Great care was taken to exploit Crystal Ball and @Risk's correlation capability. Crystal Ball has the nicest correlation matrix utility making it very easy to explicitly assign the "exact" cross correlations for this case study. Crystal Ball was able to emulate the input correlation matrix quite a bit better than ACE. However, in this particular case study, we will see that the simplified approach used by ACE does not impact the cost results significantly.

In addition to the above correlation matrix, we also compared the percentile results for various homogenous correlation matrices, i.e., 0, 0.2, 0.5, 0.7, 0.9, and 1.0. The standard deviation and percentile risk results were in agreement between Crystal Ball and ACE.

We noted that all the simulation tools forecast a distribution shape for System X that does not look particularly "normal". As Figure 2 illustrates, the histogram looks more like a beta or skewed triangular distribution.

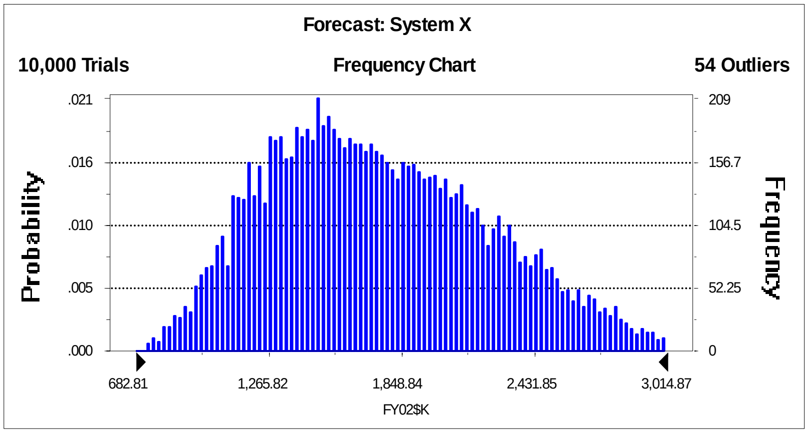

Figure 2: Probability histogram for System X from Crystal Ball.

Reference 2 assumed a normal distribution to approximate the sum of nine different triangular distributions. However, a beta approximation would be a better one to use in this case because there were so few elements and they were correlated as well. In general, we need 20 or more independently distributed items to apply the central limit theorem to the total.

As shown in Table 4, the results derived analytically based upon a beta distribution assumption outperformed the normal approximation when compared to the simulation results, especially at the end points. Note: the published median (by the normal assumption) was off by three percent and the 5th percentile was even off by nine percent when compared to the simulation results. As shown in Table 4, all the simulation tools match across all the percentile results (although @ Risk seems to be a little different to ACE and Crystal Ball at the extreme endpoints).

Table 4: MCR Case Study Risk Results

	Sd	5%	10%	50%	90%	95%
ACE	487.2	1,043	1,156	1,708	2,438	2,630
CB	486.1	1,044	1,157	1,704	2,441	2,626
@Risk	489.9	1,039	1,150	1,705	2,448	2,640
Normal	491.8	947	1,126	1,756	2,386	2,565
FRISK	491.8	1,076	1,189	1,691	2,405	2,657
Beta	491.8	994	1,121	1,729	2,431	2,610

We also noticed the sample correlation numbers by these simulation models tend to underestimate the target number on the average. For example, if the correlation coefficient between two rows is specified to be 0.7, the internal simulated numbers between these two rows is likely to derive a correlation value of 0.69.

5 COMPLICATED CASE STUDY

For completeness, we developed a far more complex, and very realistic cost model (for which no analytic risk result is possible) to compare Crystal Ball to ACE. We sequentially layered configuration risk, cost risk and correlation assumptions on the model. Table 5 shows that ACE and Crystal Ball match very well.

Table 5: Complicated Case Study Risk Results

	Standard Deviation		Mean		95th Percentile	
	ACE	**CB**	**ACE**	**CB**	**ACE**	**CB**
Config Risk	$95,199	$95,935	$526,601	$526,689	$689,995	$690,235
Config Risk, Config Corr	$104,739	$104,749	$526,047	$525,764	$709,903	$708,328
CER Risk, Config Risk, Config Corr	$116,760	$116,886	$526,711	$527,316	$732,412	$735,483
CER Risk, CER Corr, Config Risk, Config Corr	$188,446	$185,434	$533,537	$533,843	$875,281	$872,692

CONCLUSIONS

We have conducted the cost risk analyses for several published risk sessions and compared the risk results from ACE, Crystal Ball, and @Risk to analytic solutions. The risk statistics are very consistent across these different simulation models.

We regularly get questions from Crystal Ball users wanting to know why ACEIT produces “different” answers when compared to Crystal Ball. There can be many reasons. For example, if your point estimates were derived from CERs, then you need to define the equation (CER) and the corresponding error term in two separate cells when using CB, and then store the result of their product (if errors are multiplicative) in a third cell, which is termed a “forecast” cell. If you have factor equations in your model, you must ensure they are linked to the forecast cells instead of the CER cells. Otherwise, the simulated sample standard deviations will underestimate their true values. You can find other tips for using Crystal Ball in the cost environment in Appendix A.

The internal ACE, CB, and @Risk results for all iterations were also extracted in order to calculate the actual correlations between the WBS elements. ACE ships with an Excel tool to facilitate this. When evaluating the sample correlations from these simulation tools, we noticed these simulated numbers tend to underestimate the target numbers on the average. In general, all the tools establish a correlation that is 1 to 2% less than the target. ACE uses a Pearson Product Moment correlation algorithm. Crystal Ball and @Risk use the Rank Order correlation. Despite this difference, in the typical cost estimating environment, it often does not seem to matter (all get remarkably similar percentile cost results).

APPENDIX A: TIPS FOR USING CRYSTAL BALL IN THE COST ENVIRONMENT

Truncation:
If the mean cost of an item is $10K but the distribution is so wide it can be +/- $15K, Crystal ball defaults to allowing negative values. ACEIT does not. For any cost item, ACEIT truncates at zero by default. (We do not think an item can be any cheaper than free.) Although you can manually ask Crystal Ball to truncate at zero, most users forget to do it.

Risk on Top of Risk:
The most common application of Crystal Ball is to set up the cost equations and apply distributions to the inputs. Most users forget that the CERs themselves have (often more) uncertainty, either additive or multiplicative. It can sometimes be tricky to ensure risk on risk is applied correctly.

Seed:
Crystal Ball allows users to specify the initial seed value under “Run Preferences.” The user doesn’t have access to the seed values for all the assumption cells. As a result, the risk results in CB may change simply by rearranging the WBS elements.

Correlation:
If you create several worksheets in the same workbook all containing correlation matrices, they (or the user) can become confused.

Point Estimate

Crystal Ball automatically updates the input cost, i.e., point estimate, to reflect the distribution mean once the risk parameters are specified. Therefore, the point estimate for the assumption cell may be changed by this feature. It is recommended to have a separate cell in CB to store the point estimate, especially when the distribution bounds are tied to this value.

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BIOGRAPHIES

Alfred Smith: General Manager for the Software Products/Services Group. Over 20 years experience leading, executing or contributing to life cycle cost model development for wide variety systems such as Aircraft Carriers, Submarines, Multi Mission Aircraft, Amphibious Assault Vehicles, International Space Station and Customs Modernization. 10 years experience teaching cost estimating, statistical analysis and risk modeling. Tecolote lead for the development, distribution and support of the ACEIT suite of tools. Education: 1986 University College, London, England, Master of Science with Distinction; 1978 Royal Military College, Kingston, Bachelor of Engineering. **Tel:** (805) 964-6963, **E-mail**: asmith@tecolote.com

Dr. Shu-Ping Hu: Principal analyst at Tecolote Research, Inc. Tecolote's expert in all statistical matters since 1984 and principal resource for the design, development, modification, and integration of statistical software packages Tecolote has developed to conduct regression analysis, learning curve derivation/implantation, and cost risk analysis. Over 15 years experienced developing independent cost estimates, cost analysis research, and risk analysis implementation. Advocated an iterative regression technique (MUPE) to model a multiplicative error term without bias, developed correction factors (PING Factor) to adjust for the downward bias in log-error models and principal developer of the correlation method implemented in the ACE simulation method. Education: 1975 National Taiwan University, BS – Mathematics; 1981 University of California at Santa Barbara, MS – Statistics; 1983 University of California at Santa Barbara, Ph. D. – Statistics. **Tel:** (805) 964-6963
E-mail: shu@tecolote.com