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Performing Statistical Analysis on Earned Value Data

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Biographies

Eric R. Druker CCE/A graduated from the College of William and Mary with a B.S. in Applied Mathematics in 2005 concentrating in both Operations Research and Probability & Statistics with a minor in Economics. He is employed by Booz Allen Hamilton as a Senior Consultant and currently serves on the St. Louis SCEA Chapter's Board of Directors. Mr. Druker performs cost and risk analysis on several programs within the Intelligence and DoD communities and NASA. He was a recipient of the 2005 Northrop Grumman IT Sector's President's award and the 2008 TASC President's award for his work on Independent Cost Evaluations (ICEs) during which he developed the risk process currently used by Northrop Grumman's ICE teams. In addition to multiple SCEA conferences, Eric has also presented papers at the Naval Postgraduate School's Acquisition Research Symposium, DoDCAS and the NASA PM Challenge. He has also performed decision tree analysis for Northrop Grumman Corporate law, built schedule and cost growth models for Hurricane Katrina Impact Studies and served as lead author of the Regression and Cost/Schedule Risk modules for the 2008 CostPROF update.

Dan J. Demangos has over 16 years of professional experience in Earned Value Management (EVM) setup and implementation, planning & scheduling, schedule/cost integration, and Project Management training development and delivery. Mr. Demangos' clients include FBI where he manages the implementation of an ANSI-748 compliant EVMS; DHS where he led a team that supports budget, acquisition and EVM efforts for the Office of the CIO; and the US Marine Corps. where he led the effort to implement EVM throughout the Budget Department of the Marine Corps. Headquarters. Mr. Demangos has also lead a team to rewrite Booz Allen's Management Control System Description (MCSD) and has developed a phased training program that is offered to those in the Firm who practice EVM. Mr. Demangos was also a key contributor to the industry recognized AACE Earned Value Professional (EVP) certification and serves on the Certification Board. Prior to coming to Booz Allen, Mr. Demangos led the Project Controls effort for a telecommunications provider, implemented schedule/cost integration efforts for a Project Management software vendor and helped to manage remediation sites for the Department of Energy.

Richard L. Coleman is a 1968 Naval Academy graduate, received an M. S. with Distinction from the U. S. Naval Postgraduate School and retired from active duty as a Captain, USN, in 1993. His service included tours as Commanding Officer of USS Dewey (DDG 45), and as Director, Naval Center for Cost Analysis. He has worked extensively in cost, CAIV, and risk for the Missile Defense Agency (MDA), Navy ARO, the intelligence community, NAVAIR, and the DD(X) Design Agent team. He has supported numerous ship programs including DD(X), the DDG 51 class, Deepwater, LHD 8 and LHA 6, the LPD 17 class, Virginia class submarines, CNN 77, and CVN 78. He is the Director of the Cost and Price Analysis Center of Excellence and conducts Independent Cost Evaluations on Northrop Grumman programs. He has more than 65 professional papers to his credit, including five ISPA/SCEA and SCEA Best Paper Awards and two ADoDCAS Outstanding Contributed Papers. He was author of the Risk Module and a senior reviewer for all the SCEA CostPROF modules and its successor CEBoK. He has served as Regional and National Vice President of SCEA and is currently a Board Member. In 2008, he received the SCEA Award for Lifetime Achievement

Abstract

Traditional Earned Value Methods, such as those described in the equations on the DAU Gold Card, suffer from the shortcoming that they do not allow for inferential or descriptive statistics. The Estimates at Completion (EAC) they yield can therefore not be evaluated for bias or uncertainty, nor can statistical significance tests be applied to them. This leads to the propensity for these estimates to tail-chase, meaning that the EAC for an over running program will systematically lag in predicting the overrun, and the EAC for an under running program will systematically lag in predicting the under run. Lastly, without quantified uncertainty measures, there is no method by which to perform risk analysis on these estimates without relying on subjective methods.

The purpose of this paper is to present a method by which statistical analysis techniques can be applied to Earned Value data to better predict the final cost and schedule of in-progress programs. EACs developed using statistical methods rely on historical data and are thus testable, that is to say that they can be subjected to statistical significance tests, and are thus defensible. Estimates produced using statistical analysis techniques will be unbiased and the descriptive statistics developed as a byproduct of the method will allow uncertainty to be quantified for risk analysis purposes. Lastly, because this method normalizes out shifts in the CPI (or SPI for schedule estimates) that seem to be pervasive among similar programs, productivity can be monitored with a high degree of accuracy. These methods can be applied at any level, from the program office to the CAIG, to develop more accurate estimates.

For demonstration, the method will be applied to a set of representative data. The paper will continue with an example of the paradigm shift this type of analysis caused when it was implemented across a production facility. The conclusion will discuss the types of data needed to implement this type of analysis/process.

Introduction

Currently, Earned Value Management calculations suffer from several shortcomings that lessen their viability as a cost estimating tool. Most importantly, estimates developed using most EVM equations are subject to tail-chasing whenever the CPI changes throughout the life of a program. Tail-chasing is when the EAC for an over running program systematically lags in predicting the overrun, and vice-versa. This occurs because these equations are backwards looking in regard to CPI; they lack the ability to predict changes in the CPI looking forward and thus fail to perceive trends. Trail-chasing is thus inevitable because, as Christensen wrote: "in most cases, the cumulative CPI only worsens as a contract proceeds to completion."[1]

In addition to their propensity to produce EACs that tail-chase, earned value calculations also suffer from the shortcoming that they use simple algebra, not statistical analysis; thus their EACs are not unbiased, testable or defensible. Bias is the difference between the true value of an estimate and the prediction using the estimator. Unless an estimate is proven to be unbiased, it cannot be asserted that it is truly the "most likely" cost estimate. Testable estimates are those which can be subjected to decisions based in measures of statistical significance. When a desired level of statistical significance has been reached, the estimate is defensible.

Lastly, because traditional earned value calculations do not rely on statistical analysis, there is no quantitative measure of the uncertainty in the estimate. Because of this, the only way to perform quantitative cost risk analysis around estimates made using these calculations is to use subjective inputs.

Performing Statistical Analysis on Earned Value Data

Performing statistical analysis on earned value data solves all of the aforementioned shortcomings. Most importantly, EACs developed using statistics include a forecast for the final CPI, are unbiased and thus are not subject to tail-chasing. Similarly, because estimates developed using statistical techniques are based on historical data, they are testable and defensible: measures of statistical significance can be used to defend the estimate. Quantitative risk analysis can be performed using the uncertainty measures that are byproducts of the statistical analysis. Lastly, the statistical methodologies discussed in this paper can be applied alongside traditional earned value methods and easily incorporated into the EVM process as a cross-check of the calculated estimates. Once the statistical analysis has been performed once, the estimates it produces can be updated with very little recurring effort. Although not discussed within the context of this paper, similar methods can be applied to the SPI to develop statistically based schedule estimates.

The authors believe that there are several reasons that the types of analysis about to be discussed have yet to be widely applied to EVM data. First, because EVM was developed as a program management technique for measuring progress in an objective manner, it traditionally falls within the realm of program management or financial controls, not within the realm of cost analysis. Unfortunately, the techniques needed to perform statistical analysis, which are typically performed by cost analysts, can be mathematically complicated, especially when there are events such as rebaselining involved. Additionally, the patterns this type of analysis looks for within the EVM data are generally not visible using standard techniques such as scatter plotting. Lastly, from a

[1] (Christiansen, 1994)

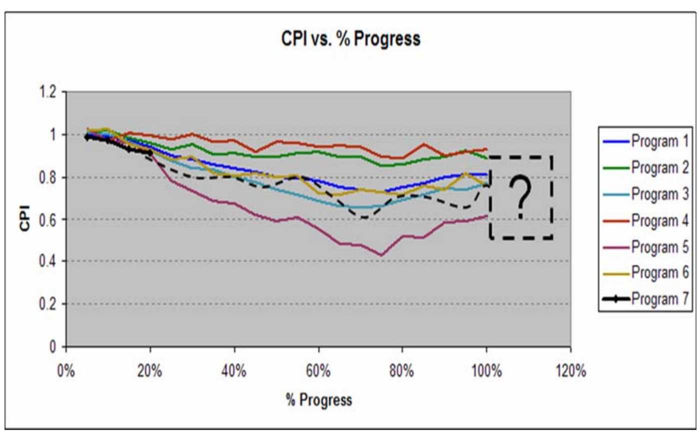
cost estimator's perspective, it is difficult to acquire the data needed to perform statistical analysis EVM analysis because there aren't many databases dedicated solely to historical EVM data. Data collection/normalization often ends up being the most time consuming part of this type of analysis.

Despite the difficulties in applying statistical analysis techniques to EVM data, the ability to produce defensible, unbiased estimates that include risk analysis and don't tail-chase is well worth the effort

The Methodology

The overarching theory behind statistical EVM analysis is that programs of a similar nature, or performed by a similar contractor, can be used as a basis to project patterns in the CPI over time. Perhaps the programs that best personify this are ship production programs. One thing common to all ship production programs is that the CPI almost always drops over time. This occurs because as the ship moves from the shop, to the blocks, to the yard, work becomes more difficult to complete because workers move from working at a workbench (at the shop) to working at their feet when the unit is being assembled upside-down, to working above their head when the ship is in dry-dock or the water. Looking only at the current, or average, CPI, estimates for these ship production programs would always tail-chase. If one could somehow predict the systemic CPI drop prior to it occurring, a more accurate EAC could be developed. To see how to do this, an example analysis using representative data will be performed. Following this, results from a real-world implementation of this method at a production facility will be examined.

Figure 1 charts the CPI over the lifespan of 6 completed programs as well as the latest reported CPI for in-progress program 7. Examining the lines, it is not apparent that there is any trend that would yield any information applicable to estimating program 7. Figure 1 also shows the latest EVM report for program 7.



Program 7	
BCWP	$ 20
BAC	$ 100
% Progress	20%
ACWP	$ 22
CPI	0.91

Figure 1 – CPI Over Lifespan for Historical Programs

When regression analysis is performed on the historical data (programs 1 through 6) it is revealed that there is a significant relationship between a program's final CPI and its CPI at 20% progress. This implies that a program's CPI at 20% progress can be used to estimate its final CPI. This CPI, along with the most up-to-date BAC, can be used to derive a statistically based EAC. The next step is to apply this relationship (shown in Figure 2) to the latest available EVM data from program 7.

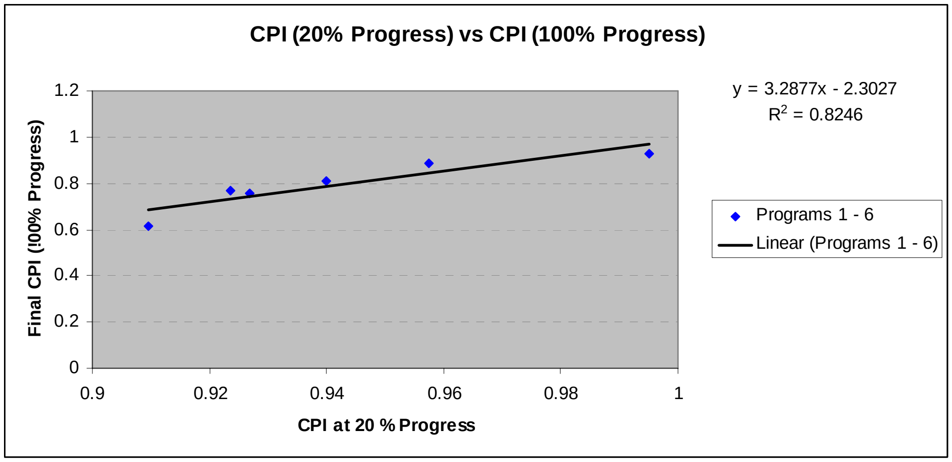
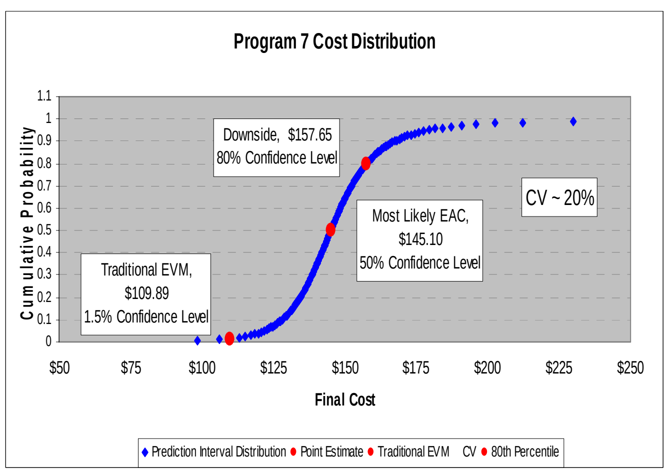


Figure 2 – Regression of Final CPI vs. CPI at 20% Progress

Using the knowledge gained from the regression analysis, a predicted final CPI of 0.69 (rather than the current reported CPI of 0.91) is applied to the BAC. This EAC differs dramatically from that produced using traditional EVM calculations. More importantly, because regression analysis was used, the EAC is statistically significant, unbiased, and includes the uncertainty measures needed for quantitative risk analysis. Figure 3 shows the probabilistic cost estimate (S-Curve) for program 7, as well as the estimate developed using the traditional calculation from the Gold Card.



Program 7		
BCWP	$	20
BAC	$	100
% Progress		20%
ACWP	$	22
CPI		0.91
Traditional EVM		
EAC	$	109.89
Statistical EVM Analysis		
Predicted Final CPI		0.69
EAC	**$**	**145.11**

Figure 3 – Probabilistic Cost Estimate Including Uncertainty Measures from Regression Statistics

Statistically Based EACs vs. Calculated EACs

The previous section provided an example for how estimates can be developed using statistical analysis. Comparing how this estimate changes over time to how a traditional, calculated EAC changes over time, as new data is released demonstrates how using statistical analysis eliminates the propensity for estimates to tail-chase. Although this data is representative, the results being demonstrated are similar to what has been experienced when the method is applied to real-world programs.

Figure 4 shows how the statistically derived EAC compares to the calculated EAC (using the gold card best case equation[2]) at each 20% of progress. Notice how the statistically derived EAC remains stable while the calculated EAC changes from release to release. This is an example of the calculated EAC tail-chasing because it is not an unbiased estimator. The statistically derived EAC does not change because the regression analysis performed in the previous section has revealed trends throughout the life of the program in the CPI. The analysis then normalizes the estimate for changes in the CPI that should be anticipated to ensure an unbiased EAC. This means that so long as Program 7 behaves similarly to the historical programs in its CPI trends, the statistically derived estimate will not change.

Program 7	% Progress					
	20%	40%	60%	80%	90%	100%
BCWP	$ 20	$ 40	$ 60	$ 80	$ 90	$ 100
BAC	$ 100	$ 100	$ 100	$ 100	$ 100	$ 100
% Progress	20%	40%	60%	80%	90%	100%
ACWP	$ 22	$ 54	$ 96	$ 131	$ 136	$ 145
CPI	0.91	0.74	0.63	0.61	0.66	0.69
Traditional EVM						
EAC	$ 109.89	$ 135.94	$ 159.36	$ 164.05	$ 150.68	$ 145.11
Statistical EVM Analysis						
Predicted Final CPI	0.69	0.69	0.69	0.69	0.69	0.69
EAC	**$ 145.11**	**$ 145.11**	**$ 145.11**	**$ 145.11**	**$ 145.11**	**$ 145.11**

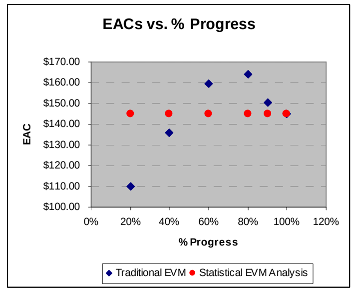


Figure 4 – Statistically-based EACs vs. Calculated EACs Over Time

Data Requirements

In order to perform statistical analysis on EVM data, there are several important data requirements. The critical data required is progressing data from completed programs of a similar nature. Examples of programs that would be of a similar nature include those which are performed by the same contractor as is performing the work in question as well as those that would be considered close enough an analogy to include in a CER. The most obvious set of progressing data is earned value reports, but any dated cost report with an estimated completion date will do. The key is that the data allows a measure of progress to be developed (ex: percent of estimated schedule, percent of final schedule, BCWP/BAC, milestones such as PDR, CDR, etc.) The ideal data is that which has progress measures such as first flight or launch where there is a dependable measure of progress. The most difficult step in this method, besides data collection, is data analysis. Tools such as dummy variables can be used to handle events such as rebaselinings that, although common among programs, can lead to discrepancies in the analysis if not handled correctly.

[2] Gold Card Best Case Equation: EAC = ACWP + (BAC – BCWP)/CPI

Statistical Analysis and the EVM Process

The aforementioned techniques can be easily incorporate to fit within the EVM process. Due to the comparably high start-up cost for developing statistically-based EVM estimates (generally 1-3 weeks *after* the collection of historical data is complete), these methods are best applied when there is low confidence in the currently available estimates. This could be caused by the EAC demonstrating tail-chasing tendencies or a significant variance between the grassroots estimate and the calculated EAC.

Once the statistically-based estimate is available, it provides an independent crosscheck of the available estimates. After the statistical analysis is complete, the recurring cost to update the estimate is minimal (4 hours – 1 day). Updating the statistically-based estimate may not even be necessary if it verifies one of the original EACs when it is first developed.

The next section will show the success of this method when applied across a production facility. It is taken in large part from the paper *Ending the EAC Tail-Chase: An Unbiased EAC Predictor Using Progress Metrics*.

A Real World Example: Progress-Based EACs

In 2006, a client was facing a two-fold problem in estimating the final cost of production units at their facility. First, estimates using the EVM calculations were found to tail-chase (every time an EAC was reported, the latest EVM metrics would already yield an increase above and beyond that EAC) and were viewed with wide skepticism both within the company and by their government client. Making matters even more difficult, a natural disaster had recently occurred at the production facility causing a sharp and prolonged decrease in productivity.

The PM for one of the programs at this facility reached out to see if there was a way to develop more accurate and defensible estimates than were currently available. The resulting analysis represented the author's first experience with performing statistical analysis on EVM data. This specific implementation is known as the Progress-Based-EAC method.

The key difference between this analysis and the example in the previous section is that in this case the final cost was regressed against ACWPs at various progress points (as opposed to the final CPI being regressed against the CPI at various progress points). To begin, as-reported EVM data was gathered for all units of the same type being estimated that had been produced at the facility. The ACWP at intervals of 10% progress was scatter plotted on a chart to see if any patterns were visible (Figure 5)

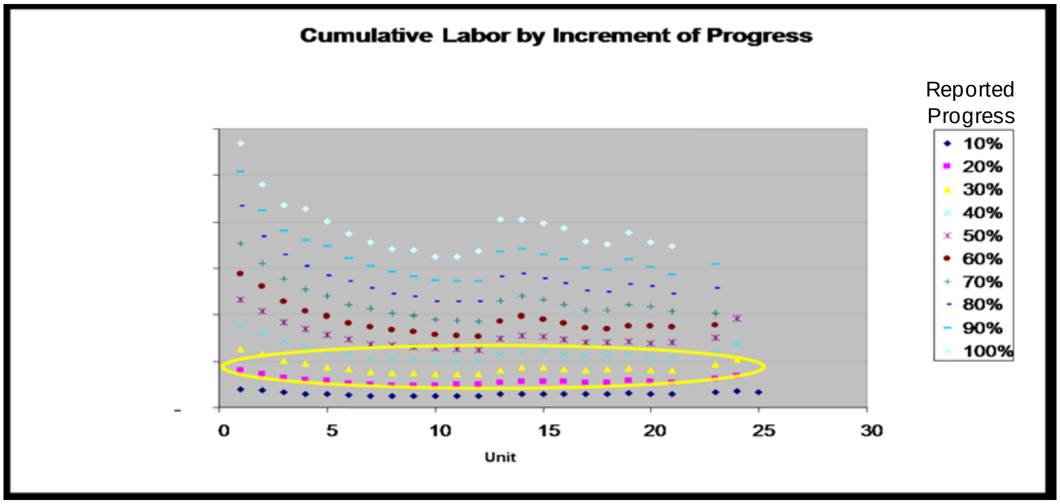


Figure 5 – Cumulative Labor by % Progress for 25 Units

When the above scatter plot was examined more closely, it became immediately apparent that the pattern in the points representing the final cost of each unit was visible as early as 30% progress. This can be seen when units 12 through 20 are examined closely in Figure 6. These units were in production during a period during which the facility experienced unexplained cost growth on many of their units. In many of these cases, this growth was not recognized until the unit was significantly along in its production cycle. From this graph it is apparent that had the facility compared the ACWP of any two units at equal percent progresses, they would have been able to predict at least relative cost growth. This chart lead to regression analysis being performed on the EVM data.

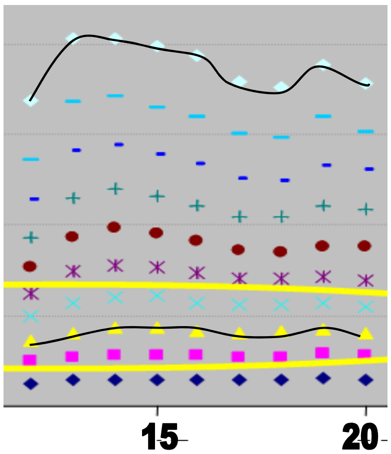


Figure 6 – Zoomed in Cumulative Labor by % Progress for Units 11 through 20

Regression analysis was performed to answer the question: Can the final cost of a unit be predicted knowing only its ACWP at a certain percent progress? At each 10% increment of reported progress, the final cost was regressed against the ACWP. At 20% the first significant regression was found with an *unbiased* error of 4%. This lead the team to conclude that *by 20% progress, the facility could predict the cost of any unit, unbiased,± 4%*. Additionally, the further along a unit was in its production, the less the error. A sample regression is shown in Figure 7.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.956210345
R Square	0.914338224
Adjusted R Square	0.90982971
Standard Error	
Observations	21

ANOVA

	df	SS	MS	F	Significance F
Regression	1	6.13857E+12	6.139E+12	202.80255	1.36728E-11
Residual	19	5.75105E+11	3.027E+10		
Total	20	6.71368E+12			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept			0.5815324	0.5677177				
20%			14.240876	1.367E-11				

Figure 7 - Sample Regression

With the success of the regression analysis, further work was done to gain more insights into the results. The next step was to perform a "regression of regressions." Each of the previous regressions was of the form: Final Cost = *A* * $ACWP_{\% \text{ Progress}}$ + C. After taking a look at the results, the intercept was removed from the regression[3] to produce the equation: Final Cost = *A* * $ACWP_{\% \text{ Progress}}$. In essence, "*A*" represents a "multiplier" that can be used to extract the final cost of any unit given an ACWP and associated progress. 1/*A* also represents the true percent progress in terms of cost.

With the above regressions replicated for each 10% of progress, the *A* term was charted against its associated % reported progress (Figure 8). These plots were developed for two types of units with different schedules, costs and physical parameters. Shockingly, the lines representing the *A* multiplier for two types of units were found to be *exactly the same*.

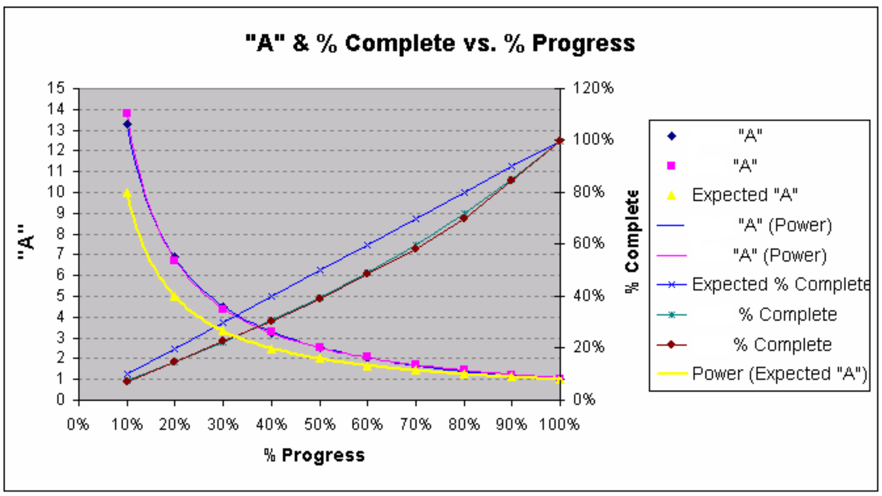


Figure 8 - "*A*" Multiplier and % Complete (Cost) vs. % Progress

Several breakthrough insights were gained through the above graph:

[3] In almost every single case, the authors strongly advise against removing the intercept from a regression. It was done specifically in this case to allow the slopes ("A") to be regressed against the % progress for the "regression of regressions"

1. As the % complete (in terms of cost) vs. % reported progress line is non-linear, the facility's EACs (using traditional EVM) must tail-chase as the CPI is always degrading.
2. The *A* multiplier for both types of units produced at the facility follow the exact same curve, meaning that the same curve can be used to estimate multiple unit types, even if those unit types were not included in the analysis. This fact was proven to be true over the next two years.
3. Each % progress cost progressively more as the unit moves along in production

To estimate the final cost of a unit, the *A* multiplier for the current % progress is found from Figure 8. The current ACWP is then multiplied by *A* to find the EAC. For example, an ACWP of $50 at 10% would yield an estimate of: $50 * 13.2 = $690.

As the cost per 1% progress rises throughout construction, traditional EVM calculations can never produce an accurate EAC. This is because the degrading CPI leads to consistent tail-chasing. Fortunately, this degradation is predicable a-priori (using the previous regression method) which is why the method works. The multiplier curves can be used to predict the ACWP at a future % reported progress. Comparing the actual ACWP to this prediction provides a method by which productivity can be monitored.

Summary: Progress-Based EACs

This method is a wholly-data-based method of EAC projection that relies upon progress and man-hour data alone. The model is:

1. Able to project EACs for all unit types at the facility within about 2% - 5% after about the 20% progress point
2. Able to work incrementally projecting work remaining given MH
3. Able to include uncertainty with the estimate because it is statistically based
4. Unbiased – the error is symmetric … specifically, it does <u>not</u> result in a tail chase

Outside the scope of this paper, but just as important. Because the model can be used to predict future ACWPs, it can also be used to monitor productivity and measure the cost of events that cause drops in productivity.

In the case of short term events, the model, because it is progress based, is able to separate out specific effects such as additional costs due to a fire or other exogenous event for units that were at least 20% complete before the event. This "effect cost" is obtained by subtracting the would-have-been cost from the actual final cost of the unit. In the case of long-term effects, because of its incremental ability, the model is able to add actuals up to an event, and, since it can predict ETC after any post-event increment of about 20% of progress has occurred, can predict ETCs after the event.

This analysis proved nothing short of revolutionary for the client who had programs that had experienced multiple rebaselinings. To date, the method has correctly estimated the final cost of all 4 units it has been applied to. In 2006, midway through the production effort one of these units, the Progress-Based EACs method forecasted 60% cost growth for the program. This cost growth was predicted prior to the latest program estimate recognizing *a single dollar of cost risk*. After significant resistance, it took a full 2 year (till 2008) before the program team recognized that 60% cost growth was even feasible. It took another 6 months (into 2009) before the program team recognized that 60% cost growth was, in fact, accurate.

Following its success, the method's use was expanded. The analysis is now performed on all in-progress programs and the results are presented to executive management regularly. The method is also used to monitor productivity on all in-progress programs.

Conclusion

Performing statistical analysis on EVM data provides an invaluable capability in that:

1. CPI forecasts can be developed, thus avoiding the problem of tail-chasing when estimates are developed using only backwards looking equations
2. The EACs developed using statistical methods are unbiased, testable, and defensible
3. The uncertainty in the estimate, for use in risk analysis, is automatically included with statistically based EACs
4. The analysis can be incorporated into the EVM process to provide a third data point in addition to the calculated EAC and grassroots estimate

Despite the utility of methods such as these, there are still hurdles to overcome before they can be widely implemented. EVM data from completed programs must be compiled and provided to cost estimators and cost estimators must become more involved in the EVM process.

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